THE INCOME-HEALTH GRADIENT IN CHILDHOOD

ESSAYS ON

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Abstract

This dissertation is comprised of three essays, the goals of which are to provide an empirical understanding of how the income-health relationship evolves with child age and the underlying mechanisms. Previous research, conducted in US and Canadian settings, has found a positive association between household income and child health, which strengthens with age. One reason for this relationship may be that low-income children are more likely to suffer from chronic conditions than high-income children. While US research has controlled for the effects of parental health when examining the gradient, Canadian work has not. In Chapter 1, we seek to determine whether the Canadian findings persist after controlling for parental health status. Our results show that this adjustment reduces the size of the gradient in childhood and, importantly, indicates that it does not increase with age. In Chapter 2, we contribute to this literature by applying more flexible estimation techniques, namely nonparametric models, to understand the gradient in childhood. Our results provide evidence that our nonparametric model is closer to the true data generating process than the parametric model. Furthermore, our estimates confirm that the gradient does not increase with age, regardless of whether we control for parental health. In Chapter 3, we examine the relationship between family income, chronic conditions and child health. Generally, our results suggest that income does not have a significant impact on chronic conditions. Furthermore, we do not find the effect of chronic conditions on the probability of being in poor health differs by income levels, with the exception of asthma and mental handicap.

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Introduction

In the health economics literature, it is well documented that wealthy people live longer and exhibit lower morbidity and mortality rates compared to the general population. However, the positive correlation between income and health is not limited to individuals at the upper tail of the income distribution only. Indeed, the *gradient* in health status – the phenomenon that relatively wealthier people have better health and vice-versa – is evident throughout the entire income distribution.

There has been considerable research on the relationship between income and health. For example, Smith (1999) finds that across all age groups for adults 25 to 54, those in excellent health have 74 percent more wealth than respondents in fair or poor health. However, the reasons for the relationship are less clear since plausible causal mechanisms run in both directions. On one hand, wealth could grow more rapidly among those who start in better health because good health increases future earnings capacity and facilitates savings. On the other hand, more economic resources could protect individuals from illnesses so that their subsequent health is better.

This simultaneity issue has prompted authors to look at data on children in order to find the antecedents of this relationship or, in other words, the "origins of the gradient". One reason why this approach is particularly attractive is that, within the context of the developed world, children's health is assumed to have relatively little or no impact on the socioeconomic status of the household they live in. Thus, the issue around the income-health causality found in adulthood disappears when we work with child data.

Case, Lubotsky and Paxson (2002) were the first authors to explore this issue. Their paper, "Economic Status and Health in Childhood: The Origins of the Gradient", published in the American Economics Review, is a seminal article on this topic. One of the main objectives of this paper is to understand whether the income-health relationship, that is, the gradient, also holds in childhood. Using American cross-sectional data, the authors find evidence of a positive relationship between child health and household income, one which becomes stronger as children age. In addition, they find that children's health is closely related to long-run household income and that the adverse health effects of lower permanent income increases as children become older.

Following Case et al's (2002) work, Currie and Stabile (2003) also published a paper in the American Economic Review, entitled "Socioeconomic Status and Health: Why is the Relationship Stronger for Older Children?". Using longitudinal data from Canada, and based on the work by Case et al. (2002), Currie and Stabile (2003) find that the income-health gradient for Canadian children behaves in a similar manner to the one found in the US.

The first chapter of this dissertation revisits Currie and Stabile's (2003) paper by proposing a new framework to examine the relationship between child health and household income and how it changes with child age. Our findings suggest that the income-health gradient for Canadian children is constant with age, contrary to previous work in the literature. In other words, we find that the difference in health status between high- and low-income children does *not* increase throughout childhood. This result is due to the inclusion of parental health status in our model.

Following Case et al.'s (2002) methodological approach, all subsequent research on this topic has employed a standard ordered probit specification to estimate the child health/household income relationship. This model is commonly used in the economics literature to examine ordered outcomes, such as self-assessed health status. One of the key assumptions of the ordered probit is that the error term is normally distributed. Moreover, this model includes several other assumptions, which can pose serious limitations to the analysis of an ordered dependent variable and bias results.

To overcome this issue, some authors have suggested the use of more flexible estimation techniques, namely nonparametric methods (Li and Racine, 2007). The use of these techniques may add to this literature, since they are robust to misspecification. Furthermore, the use of nonparametric estimation methods has been shown to reveal important structure in the data that may not be captured by traditional parametric models (Li and Racine, 2007).

In the second chapter of this dissertation, we find that our proposed nonparametric model provides an improvement over its parametric counterpart, providing evidence that the former one is closer to the true data generating process than the latter one. Furthermore, our estimates confirm that the gradient does not increase with age, regardless of whether parental health is included in the model.

One important question within the context of this literature is why high-income children differ from low-income children regarding their health status. Case et al. (2002) investigate whether the accumulation of chronic conditions plays a role in explaining the income-health gradient. Moreover, they explore a series of other mechanisms which could potentially be behind this relationship. They find that the arrival and impact of chronic conditions explain, in part, the health disparities between high- and low-income children. In addition, Case et al. (2002) are able to rule out several possible mechanisms such as health status at birth, health insurance and genetics.

Currie and Stabile (2003) also try to identify the mechanisms underlying the health differences between high- and low-income children. They find that these differences can be explained by the fact that low-income children are less able to respond to a given health shock (in the form of a chronic condition and/or an episode of hospitalization), so that the negative effects of health shocks persist and accumulate over time. However, with the exception of asthma, the impact of chronic conditions on child health was not examined individually, but rather jointly in the form of a health shock. Thus, the impact of specific chronic conditions as well as activity limitations on children's health status has not been fully explored within the Canadian context.

In the third chapter of this dissertation, we extend Currie and Stabile's (2003) analysis by examining the role of chronic conditions and activity limitations on child health and whether the impact of the former on the latter differs by income levels. We find that income does not have a significant impact in explaining the prevalence of child chronic health conditions. Moreover, we do not find that the effect of chronic health conditions on the probability of being in poor health differ with income levels, with the exception of asthma and mental handicap.

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Chapter 1

Understanding the Income Gradient in Children's Physical Health: Revisiting the Canadian Case

1.1 Introduction

The positive relationship between socioeconomic status (SES) and health is one of the most robust and well-documented findings in economics. The income-health gradient has been observed to increase with age, at least until about age 50 (Smith, 2005). Furthermore, it is not only a middle- or late-life phenomenon, since it appears for some in their early years of labour force activity and emerges for others as their economic resources and health increasingly interact over their lives (Smith, 1999). However, why such a relationship should hold is not clear since plausible causal mechanisms could run from health to SES or in the opposite direction - or both.

In recent years, the search to disentangle these effects has included work with data on children in order to find the origins of the gradient. Such analyses are motivated by the fact that the health of children can be assumed to have little impact on their own SES but the SES of the households in which they live could affect their health. The effects of health have profound consequences that last over the life course - poor health in childhood is associated with lower educational attainment, inferior labour market outcomes and worse health in adulthood. Thus, it is important to have a clear understanding of the origins of the gradient as one of the factors that furthers or hinders intergenerational mobility. From a policy perspective, it is important to understand how health inequalities arise and what can be done to reduce them.

In recent years, economists have tried to understand the relationship between family income and child health. Those that have made strong contributions to the field, include Case et al. (2002), J. Currie and Stabile (2003) and A. Currie et al. (2006), among others. In an influential paper, Case et al. (2002) find that there is a positive relationship between child health and family income using American cross-sectional data. Furthermore, they find that this relationship is stronger as children age. Using the same methods as Case et al. (2002), J. Currie and Stabile (2003), hereafter C&S (2003), and A. Currie et al. (2006) also examine this relationship using Canadian and British data, respectively.

For the US and Canada, the authors find that the income-health gradient is large and increases as children age. In Britain, the evidence suggests that the income-health gradient in childhood is smaller than that found in the US and Canada. Furthermore, there is no clear pattern of how this relationship changes with age.

While Case et al. (2002) and A. Currie et al. (2006) both examined the impact of the inclusion of parental health status in their models, C&S (2003) did not. Given that the Canadian study is lacking in this aspect, we re-examine the income gradient in children's health by proposing a new framework.

Thus, the objectives of our study are as follow: first, investigate whether, using an alternative framework, there is an income-health gradient in childhood; second, if there is an income-health gradient, understand how it changes with children's age; and third, identify the underlying mechanisms of this relationship. In order to answer these questions, we replicate and extend the work of C&S (2003), both through alternative model specifications and by making use of additional years of the National Longitudinal Survey of Children and Youth (NLSCY) data that have become available.

Our findings provide evidence that the gradient in Canada is not as strong as suggested by C&S (2003) and, furthermore, that it does *not* increase as children age. With regard to the underlying mechanisms, we find that some of the differences between high- and low-income children are due to the latter being exposed to more bad health shocks. Moreover, we provide new evidence that parents' health status plays an important and independent role in explaining children's health status.

In what follows, we undertake a review and synthesis of the existing literature on the income gradient in children's physical health. We then describe the data employed in the present analyses, and highlight the methods applied. Next, we describe the results, provide some discussion of them, highlight some of their limitations and, consider their implications. Finally, we conclude with a summary of the main findings.

1.2 Literature

A distinct age pattern between income and health has been documented in the literature. Smith (2005) has found that for the United States health disparities increase with income up to age 50, after which they diminish. However, a difficulty arises in analysing the income-health gradient in adulthood, since the relationship between health and income is bi-directional. This simultaneity issue disappears for young children; since they do not work, the direction of causation is from (family) income to health status. Case et al. (2002) were the first to make use of this idea. They isolated the effects of income on the health status of children using several cross sectional data sets.

Most studies have focused on the gradient in the physical health of children. In what follows, we describe the studies selected from our extensive literature search of EconLit, REPEC and Google Scholar[1]. Only studies that analyse the income gradient in children's health in developed countries were considered. Those listed in Table 1.1 use roughly the same approach as the seminal article by Case et al. (2002), while those in Table 1.2 take on slightly different approaches. Most studies solely make

[1]The key words used in our search include "child", "health" and "income".

use of cross-sectional data to examine the income-health relationship for children. However, cross-sectional data presents some limitations when trying to explain the mechanisms underlying the relationship between household income and child health. This has led researchers to employ longitudinal data in these analyses. We describe both sets of studies in what follows.

1.2.1 Studies that Employ Cross-Sectional Data

Case et al. (2002) were the first to show that the well-known positive cross-sectional relationship between income and health observed in adulthood also exists in childhood. In their influential paper, using cross-sectional data from the National Health Interview Survey (NHIS), they find that household income is positively associated with children's health and that the strength of this relationship increases with child age, suggesting a protective effect of income on children's health status. Case et al. (2002) also find that children's health is closely related to the long-run average household income and that the adverse health effects of lower permanent income accumulate over children's lives. Using the same data, but a different framework, Chen et al. (2006) find that the gradient does *not* increase with age. In response, Case et al. (2007) demonstrate that Chen et al.'s (2006) finding is due to the inappropriate inclusion in their sample of younger college-aged adults living independently. The information available for such individuals is often a poor reflection of the SES they experienced when younger (Case et al., 2007), but has a very large effect on the estimated relationship between income and health status in the NHIS for 17 and 18 year olds.

Using British survey data, A. Currie et al. (2006) also find a positive relationship between family income and a subjective measure of child health, but in contrast to the cross-sectional results for Canada and the US, the gradient is smaller and does not increase with age. Moreover, using a variety of objective child health measures, they find *no* evidence of a family income gradient (see Table 2) and accordingly, conclude that family income is not a major factor in explaining variations in child health in England. A. Currie et al. (2006) suggest that the National Health Service (NHS) may have a protective effect on the health of children. They also provide new evidence that nutrition and family lifestyle choices have important roles in determining child health.

Propper et al. (2007) find similar evidence to A. Currie et al. (2006) using detailed data on a cohort of children up to age seven who were born in the UK in the early 1990s. Furthermore, they find that when controlling for maternal health there is almost no direct effect of income on child health. This suggests that the mother's health, specifically her mental health, plays a greater role than income in explaining the link between income and child health.

Doyle et al. (2007) are concerned that the relationship between children's health and parents' income and education is spurious, rather than causal. To explore this possibility, they undertake an instrumental variable approach. In line with other UK studies, they find a significant income gradient in child health, but no significant interaction with child age when income and education are treated as exogenous variables. However, when family income and parental education are treated as endogenous variables, the authors find larger income and education effects. They also include income squared in their models to investigate whether the effects of income are largest for the poorest children – the first in this literature to examine closely the impact of income non-linearities on children's physical health[2]. They find evidence that income effects are larger for the poor when income is treated as endogenous, but not when it's exogenous.

Using Swedish data, Nahum (2006) finds no evidence of an income gradient in children's physical health when working with objective measures of children's health status[3], such as the prevalence of chronic health conditions, hospitalisation frequency and long-term medication. This finding is in line with the A. Currie et al. (2006) results based on objective health measures. Nahum (2006) also assesses the impact of household liquidity constraints on children's physical health, using the following measures: whether the respondent can obtain 14 000 Swedish Kronas within a week if needed, either through personal savings or by other means; whether the respondent has had difficulties in paying bills in the past year; and whether the respondent has had to borrow money from friends or relatives, or request help from social assistance to pay bills in the last year. Nahum (2006) finds that children in households with any one of these liquidity constraints have a higher probability of experiencing chronic health problems. She suggests that the reforms that took place in the Swedish health

[2]This approach is commonly used in the cognitive-behavioural child health literature. Studies have shown that for a given level the impact of income plateaus (Blau 1999; Dooley and Stewart, 2004).

[3]Although these data provide information on health utilisation among children, it should be noted that this information is self-reported by the one of the parents.

care system in the late 1990's provided a more equitable supply of health services, and resulted in more similar rates of medical service use by both higher and lower income households.

1.2.2 Studies that Employ Longitudinal Data

A better understanding of how the gradient changes as children age is possible with longitudinal data, but only C&S (2003) and Link and Condliffe (2008) have explored this issue in this way.

C&S (2003) reach conclusions similar to Case et al. (2002) for Canadian children but also consider the reasons why low-income children have poorer health. On one hand, they hypothesise that low-income children are less able to respond to health shocks; on the other hand, they suggest that low-income children are more likely to experience bad health shocks. C&S (2003) find that both high and low-income children recuperate at the same rate, but that low-income children are subject to more frequent shocks.

Using panel data[4] on American children, Link and Condliffe (2008) replicate the cross-sectional and longitudinal approaches employed by C&S (2003). Their cross-sectional results are quite similar to those found by Case et al. (2002) and C&S (2003), thus confirming the positive relationship between child health and household income found in the literature.

[4] The authors make use of the Child Development Supplements 1 and 2 of Panel Study of Income Dynamics along with the Medical Expenditures Panel Survey for 1996-2002.

With regard to the longitudinal analysis, Link and Condliffe (2008) find evidence of a differential income effect for children in responding to a given health shock. In addition, the authors find mixed evidence that low-income children are subject to more health shocks as they become older when compared to high-income children. This effect, however, is not as strong as the one found by C&S (2003).

1.3 Data

The data used here are from Statistics Canada National Longitudinal Survey of Children and Youth (NLSCY). The NLSCY follows Canadian children's development and well-being from birth to early adulthood; the survey is conducted by Statistics Canada, in partnership with Human Resources and Social Development Canada (formerly Social Development Canada). The objective is to provide a better understanding of how various risk and protective factors affect Canadian children's development and overall well-being over time.

The NLSCY is a probability-based sample survey[5], whose target population comprises the non-institutional civilian population (aged 0 to 11 at the time of their selection) in Canada's 10 provinces. The survey excludes children living on Indian reserves or Crown lands, residents of institutions, full-time members of the Canadian Armed Forces, and residents of some remote regions.

[5]For a detailed account of the both the NLSCY methodology, see Statistics Canada and Social Development Canada (2005) Microdata User, Statistics Canada.

The first survey was conducted in 1994 and included children 0 to 11; those in the initial survey constitute the first wave. The same households are surveyed at two-year intervals, so that by the fifth wave in 2002 those in the original sample were aged 8 to 19.

The oldest children are expected to remain in the survey until the age of 25, in 2008. Additionally, children ages 0-1 have been added at each wave and retained until they reach ages 4-5, to provide a wider cross-sectional snapshot of the child population. These children are known as the Early Childhood Development (ECD) cohorts and are introduced every 3 cycles. All available cycles of the NLSCY are used in the analysis that follows[6].

The survey collects detailed information on children's health, as well as information about their families. While some questions are asked of older children (and even their teachers), most are asked of the person most knowledgeable of the child (commonly known as the PMK), usually the mother. Since the PMK reports on the subjective health measure for children up to and including age 15, we work with the sample of children present in all waves (longitudinal cohort) under age 16.

1.3.1 Measuring Health Status

While it is common practice to use self-reported measures to assess individual overall health status, children's health is typically reported by one of the parents. This

[6] At the time this paper was written, only 5 cycles were available. Since then a 6th cycle has been released.

raises concerns that the parents' reports may not be objective and may be biased by the parent's own health status. Waters et al. (2000) reviewed a series of studies in which researchers concluded that parents from all sociodemographic groups accurately and reliably report their children's developmental age, developmental problems, and behavioural problems.

Moreover, Case et al. (2002) make use of both parental and physician assessments of child health in their paper and find that the coefficients on income for physician-rated health are smaller in absolute value than those for parental-rated health, but of the same sign. This suggests that parent-assessed health is not the result of reporting bias.

Thus, our dependent variable is the PMK-reported physical health status of the child, which is available for children aged 0 to 15. The PMK is asked to rate the health of the child on a scale of 1 to 5, where 1 is excellent and 5 is poor. In addition, we examine another dependent variable – a binary variable indicating whether a child is in good or poor child health, where poor health status is defined as being in poor, fair or good health and good health is defined as being in very good or excellent health.

1.3.2 Measuring Household SES: Parental Income and Education

We now provide a description of the explanatory variables included in our model, henceforth known as the *de Oliveira model*. The main SES variables are household income and mother's education, as in the work of C&S (2003). However, we also include father's education. Including the education of both parents is important since household income may be a proxy for education. Each parent's educational attainment was classified into one of four categories (1 - less than secondary school; 2 - secondary school graduation; 3 - beyond high school; and 4 - college or university degree (including trade), where the first is the omitted case). This categorization is more refined than the dichotomization (high school education or more versus less than high school education) used by C&S (2003). Household income is reported by the PMK in dollars, and adjusted for price inflation using the Canadian Consumer Price Index. (When income is not reported, Statistics Canada imputes a value.)

1.3.3 Other Child, Parental and Household Variables

In de Oliveira model, we also control for child, parental and household characteristics: dummies to indicate child ethnicity (white vs. non-white), whether the child is first-born, whether the mother and father smoke, and whether housing conditions in which the child lives are poor. Finally, and of particular importance, we include variables measuring the health status of each parent.

1.3.4 Rationale for excluding variables from C&S's (2003) model

C&S (2003) included a dummy variable in their model to indicate whether household income was imputed by Statistics Canada. They estimated their models with and without cases for which household income was imputed, to test whether there was something peculiar about the income imputation process. Both their and our estimates were robust to these checks and, therefore, we drop the imputation dummy.

The authors also control for whether the mother is the biological mother. There is very little variation in this variable, since in 99.94% of all cases in our sample the child's mother is also the biological mother. Empirically, given the lack of variability in this variable, it does not make sense to include it in the model. Thus, we do not make use of this variable in our work.

As stated, our starting point is C&S's (2003) work; therefore, we make use of the same sample of children used in their paper (see Table 1.3 for sample means). It should be noted, however, that our sample size changes for the different models we estimate according to the availability of information. Unfortunately, not all the records for children in our initial sample possess all the variables relevant to our analyses[7].

From Table 1.3, we see that the average age of the children in 1994 was roughly

[7]For the Currie and Stabile model with parental health, we lose close to 6,000 observations, which corresponds to children that do not have information on parental health in a given cycle. For the de Oliveira model, we lose an additional 812 observations (to the previous 6,000) due to missing data.

5 years. The mean household income of the families in 1994 was about 50,000 Canadian dollars, and it increases with the cycle[8]. The incidence of asthma increases slightly, whereas GP visits and episodes of hospitalisation decrease with children's age. Twenty six percent of all children were reported to have some sort of chronic condition in cycle 1; this proportion increases over the 3 cycle period, while other health variables, such as incidence of poor health and activity limitations, remain relatively constant over time.

1.4 Methods

The income-health gradient can be understood in two ways: from either a cross-sectional or a longitudinal perspective. While cross-sectional data enables an understanding of how income and child health are related, longitudinal data can provide insight into the underlying mechanisms behind this relation.

In order to understand the causes underlying the income-health gradient, we follow the conceptual framework described by C&S. This framework is based largely on Grossman's human capital model[9] (Grossman, 1972) and is useful to understand how the income gradient in children's health changes with age. It is assumed that children are born with an initial "state of health" H_0, which is in large part determined by

[8]There is a substantial jump in the mean income from Cycle 2 to Cycle 3. We checked the data and found there was nothing peculiar with this variable.

[9]Grossman's model has not been widely used for studying the gradient between health and income. However, it has been shown that the model is in fact well suited to address these issues (Case and Deaton, 2003).

genetics and pre-natal conditions (see Figure 1.1). Children are exposed to health shocks, which may take the form of chronic conditions or diseases requiring hospitalisation. Other potential shocks could be defined as the onset of a cold or an episode of diarrhea, for example.

According to the authors, family SES contributes to the ability of a family both to detect and treat a chronic condition in the short term. In the long-run, bad health shocks dissipate and the child's health can be partially restored (Figure 1). However, it is assumed that children do not completely return to their original health status. Similar to Grossman's human capital model, this framework treats health as a depreciating stock.

In their framework, C&S (2003) distinguish two key aspects, which differentiate the health of high- and low-income children. First, low-income children do not deal as effectively with health shocks as high-income children do; this could be due to information problems or resource constraints, which may affect the treatment of health conditions. Second, low-income children are more subject to health shocks than high-income children; this higher exposure could be due to lifestyle and/or environmental conditions, such as poor housing and poor nutrition. The higher rate of health shocks will result in a steepening of the income-health gradient relationship as children age. Figure 1, borrowed from C&S (2003), illustrates the different time pattern of the health stock for high- and low-income children.

We now set out the equations that will be estimated based on the NLSCY data, while differentiating between the estimated cross-sectional and longitudinal models.

1.4.1 Ordered Probit - Pooled Cross-sectional OLS Model

The purpose of the following model is to assess how the income-health relationship changes with age, while controlling for child and family characteristics. Although we do not make use of the panel nature of the data for this model, we adjust the standard errors to account for repeated observations for the same child. We specify a Huber/White estimator (Huber, 1967; White, 1980) where observations are allowed to be independent between units of analysis, but not within them, resulting in robust standard errors. Our starting point is the replication of C&S's (2003) model,

$$health_{it} = \alpha + \beta\, ln(inc)_{it} + \gamma\, mom\, edu_{it} + \lambda\, X_{it} + \epsilon_{it} \tag{1.1}$$

where health is child health status, ln (inc) is the natural log of household income and mom edu is a dummy variable indicating whether the mother has education beyond high school. X includes a set of control variables – log of family size, mother's age at the birth of the child, year effects (year dummies), dummy variables for single years of age (cohort dummies)[10], and dummy variables indicating sex of child, whether the child belongs to a one-parent household, whether the PMK is female, whether the child's mother is not the biological mother[11], and, a variable to indicate if income was imputed. Additionally, we estimate two extensions of this model, one of which

[10]The age and cohort dummies are intended to capture both age-related changes in child behaviour and cohort effects, such as availability of treatment that might affect different cohorts.

[11]Although C&S (2003) report including a dummy variable for whether the PMK is the child's biological mother, their code shows this is not the case. In practice, the authors code this dummy variable to reflect whether the child's mother (not the PMK) is the biological mother or not.

is the de Oliveira model[12]. (Note, for the de Oliveira model X includes a different set of variables.) The subscript i denotes the individual child, while the subscript t represents the cycle in which the child is observed. This equation is estimated separately for each of four age groups (0-3; 4-8; 9-12 and 13-15), as was done by Case et al. (2002). All observations are clustered by child ID, in line with C&S's (2003) work.

1.4.2 Ordered Probit - 'Longitudinal' OLS Model

For the analyses that follow, we make use of the panel nature of the data. The basic idea of this model is to assess the differential effects of current and past health shocks on current health status by income. By distinguishing between past shocks and more recent ones, C&S (2003) investigate whether any differential effects of health shocks persist, or whether, with time, high-income and low-income children respond similarly. They estimate the following model:

$$\begin{aligned} health98_{it} &= \alpha + \delta\, shock94_{it} + \phi\, shock98_{it} + \beta\, ln(inc)_{it} + \\ &+ \psi\, ln(inc)_{it} * shock94/98_{it} + \gamma\, mom\, edu_{it} + \lambda X_{it} + \epsilon_{it} \end{aligned} \tag{1.2}$$

where health98 is a binary variable indicating good or poor child health in 1998, shock denotes a bad health shock in the indicated year[13], ln(inc) is the natural log of

[12] The other extension is C&S's (2003) model with the inclusion of parental health status.

[13] C&S excluded the "shock98" variable in their model published in 2003 but included it in their 2002 NBER working paper. We estimate both models to check the robustness to different model

the average of permanent household income, while the other variables are as defined above. All observations are clustered by family ID.

This analysis is also done for finer and broader measures of bad health shocks. The authors chose asthma as the finer measure of a bad health shock, since this is the leading chronic disease of children in the industrialised world. The broader measure is defined as both chronic conditions and episodes of hospitalisation, which allows for the fact that children may suffer long-term consequences from acute conditions, such as illness or accidents, as well as from chronic conditions. For a more detail description of this model, the reader is directed to C&S (2002, 2003).

1.4.3 Weighting

All model estimation, which follows below, is based on the use of unweighted data. There has been some debate on what estimators should be used; we provide a brief discussion. Wooldridge (2001) proposes a Hausman test to test the exogeneity of the sampling scheme. Under the null hypothesis, the sampling scheme is exogenous. This test extends the Hausman test proposed by DuMouchel and Duncan (1983) to general M-estimation[14].

Wooldrige (2001) shows that the unweighted M-estimator is consistent and asymptotically normal, and that it is more efficient than the weighted estimator under a generalised conditional information matrix equality when exogenous stratification holds. This applies to maximum likelihood estimation and, thus, to a standard ordered pro-

specifications.

[14]In practice, few authors have used this test in empirical econometrics.

bit framework. The data employed in our analyses are from the NLSCY, which uses a clustered multistage sample design where eligible households are selected from the Labour Force Survey. (For a detailed account, see Methodology of the Canadian Labour Force Survey, Statistics Canada, Catalogue no. 71-526-XPB.) Thus, individuals are sampled from selected dwellings within clusters (geographic areas) nested within provinces. The distribution of children's health is not an aspect of the sample design; thus, we conclude that stratification is not endogenous in our model.

We employ the test proposed by DuMouchel and Duncan (1983) in the context of the linear regression to help to decide whether or not to use sample weights in our multivariate analyses. This test can be described as a Hausman test of the difference between sample-weighted and unweighted regressors to test for correct model specification. In practice, each independent variable is interacted with the survey weights and a Wald test of joint significance of all the interaction terms is performed. We found that there was no clear evidence that weighting was required with C&S's (2003) model. (For two age group specifications, we found that weighting was indicated; for the other two, we found that it was not). For the de Oliveira model, we found no evidence of endogenous stratification in any of the four age group regressions[15]; hence, we present unweighted results. In the same vein, unweighted data were also used to estimate the mean values of the variables used in the analysis. STATA 9 was used for all estimation.

[15]We accepted the null hypothesis with a p-value of at least 5% for the different regressions, where the null hypothesis is that the unweighted results are consistent, i.e., that the stratification is not endogenous.

1.5 Results

1.5.1 Results from Cross-sectional Models

Estimates of equation 1.1 are presented in Table 1.4 as reported by C&S (2003). We include both Case et al. (2002) and C&S's (2003) results to remind the reader of their findings and to facilitate comparisons with our own work. Tables 1.5 and 1.6 present the results for our first extension. Once we add mother's and father's health status, we find that the income coefficients decrease substantially, though remaining significantly different from zero. The gradient previously observed by C&S (2003) continues to exist. However, we find that the increasing gradient disappears; rather, we have a constant gradient with age. These results hold when we estimate the de Oliveira model (Tables 1.7 and 1.8)[16]. Figure 1.2 plots the income coefficients for each of the various specifications, providing a picture of how the income coefficients change (the income coefficients are obtained from Tables 1.4, 1.5, 1.6, 1.7 and 1.8).

For C&S's (2003) model the income coefficients fall by 0.121 and 0.122 as children age from 0-3 to 13-15, without and with the inclusion of mother's education, respectively[17]. For the de Oliveira model, we find they fall by only half as much – by 0.065 and 0.059, without and with the inclusion of parents' education, respectively. Furthermore, for the C&S model, the income coefficients for adjacent age groups are significantly different from each other (at the 5% level for the model without mother's

[16]The models have different sample sizes due to differences in the availability of information for each child. Nonetheless, we have estimated all models using the same sample and find that our results do not change.

[17]These decreases in the income coefficients are slightly different from those found by Case et al. (2002), 0.140 and 0.104 for children 0-3 to 3-17 without and with mother's education, respectively.

education, at the 10% level with). However, when we test for the equality of income coefficients for adjacent age groups for the C&S model with parents' health and the de Oliveira model (with and without the education variables), we find no significant difference, suggesting a common gradient across age groups.

Using linear probability models, the authors find that a doubling of household income leads to an increase in the probability that the child is in excellent or very good health of 3 percentage points for ages 0-3, 4 percentage points for ages 4-8, 4.4 for ages 9-12 and 6.4 for ages 13-15. Based on the ordered probit models, we find quite different results. We focus on the change in predicted health status from age groups 4-8 to 13-15[18]. Consider a doubling of income from $30,000 to $60,000 (a change of 0.69 units in natural logs). Based on the C&S (2003) model, the probability that a child would be in excellent health increases by 5.0 percentage points for 4-8 year olds and 7.0 percentage points for 13-15 year olds. Based on the de Oliveira model, the increases are 2.5 and 2.8 percentage points, respectively. There are two points worth noting: the changes in predicted health status for the two age groups are more similar in the de Oliveira model than in the C&S (2003) model and they are at most half the size. In consequence the income-health elasticities are much smaller, suggesting that the impact of income on child health status is smaller[19].

The first-born dummy variable is significant for all age groups, except the 13-15 age

[18]We use the age group 4-8 as the basis for comparison because the coefficient for the 0-3 age group is not statistically significant in the de Oliveira model. We choose also these two age groups to have a better understanding of how health changes with age.

[19]When we move from $30,000 to $60,000, we obtain an income-health elasticity of 1.39 and 2.12 for age groups 4-8 and 13-15 respectively, for the C&S model. For the de Oliveira model, we find an income-health elasticity of 0.67 and 0.78 for age groups 4-8 and 13-15, respectively.

group. The birth order coefficient decreases in absolute size as we move from younger to older age groups, implying that this effect diminishes with age. The coefficient on the sex dummy indicates that the income-health gradient is more pronounced for girls but that this effect decreases in importance with age, suggesting an equalisation between boys and girls in adolescence. Furthermore, we estimate each of the four age-specific equations separately for boys and girls and find similar results. Housing conditions are significant, suggesting that children living in homes in need of repair have poorer health status.

Both mother's and father's health are positively related to children's health and significant; we also find positive and increasing coefficients in parents' health status by age group in the regressions (see Figure 1.3). However, mother's health is more strongly related to the child's health than is father's health. Furthermore, we estimate regressions where we make use of all the five health categories rather than collapsing this variable as we did previously. We find a positive monotonic relationship between mother's health and child's health – as mother's health status moved from 'poor' to 'fair' and so forth, children's health status improves[20]. For father's health, this was usually not the case. These results confirm the greater role played by the mother's health status in explaining their child's health. With regards to parents' health behaviours, we did not find parents' smoking habits to be significant. Although our models provide higher pseudo-R^2 values than those found by C&S (2003), it is useful

[20]This monotonic relationship holds for all children, with the exception of the older age group. For this group, we find that mother's health status has a positive monotonic relationship with children's health for the first two health categories (excellent and very good) only. It may be the case that for older children mother's health has a smaller impact on the child.

to note that most of the differences in children's health are not accounted for by any of our models.

Case et al. (2002) and A. Currie et al. (2006) also include controls for parental health in their models, namely self-assessed physical health status in the first case and the existence of a limiting chronic health condition in the last case. These authors find that the inclusion of these variables does not eliminate the gradient or alter the conclusions on how the income gradient changes with age. While Case et al. (2002) find that the inclusion of parents' health decreases the size of the income coefficients, A. Currie et al. (2006) find that the coefficients on income are, by in large, unaffected by the inclusion of parental health. These two sets of authors also find that impact of the mother's health is larger than that of the father.

Case et al. (2002) highlight that the inclusion of parental health status in the regression may warrant a few caveats worth mentioning. If parents' health is affected by their income, and income is measured with error, then the "effects" of parental health may simply reflect the measurement error present in the income variable. In addition, if the health of both parents and children is affected by current and lagged income, parental health may serve as a proxy for the income levels experienced by children at earlier ages. For these two reasons, it is hard to separate the effects of parents' health and family income on children's health. Thus, the inclusion of parents' health status may lead to some simultaneity issues; nonetheless, and, bearing this in mind, some authors have included these variables in their models. Ideally, one should account for parents' health status prior to the child's birth in order to avoid reverse causality (see Propper et al., 2007); however, this is not always feasible, given the available data.

1.5.2 Difference between High- and Low-Income Children

We observed that there is a difference in the health status between high- and low -income children. Yet, how does health status differ between high- and low-income children as they age? We answer this question by examining the differences in predicted health status for high- and low-income children while controlling for other observable characteristics. Our starting point is the C&S (2003) model, which we modify as follows. We redefine the household income variable to incorporate Statistics Canada Low-Income Cut-Off (LICO) measure. More specifically, for every child we calculate the 'household income to LICO' ratio for the household they belong to. This measure identifies those who are substantially worse off than the average and is based on household income, family composition and size of area of residence (this last component accounts for whether the individual resides in a rural or urban area, as well as the size of the urban area). We define low-income families as those whose total household income-LICO ratio is less than 3 and high-income greater or equal to 3[21].

Initially, we estimated the difference between high- and low-income children using the ordered probit model. We found that this model performed poorly in correctly predicting child health categories. The model predicted over 90% of the children to be in excellent health, as compared to an actual proportion of a little over 50% in our

[21]Our cut-off value of 3 is roughly 2.5 standard deviations from the mean of the income/LICO variable.

sample. This is due to the parametric nature of the model, which does a poor job in correctly predicting the outcome. Given these results, we measure health status instead as a binary variable, with categories 'good' health (= 0) and 'poor' health (=1)[22] with a probit specification. This model provides a better prediction of the outcome than the ordered probit. The difference in the average predicted health status by age group for high- and low-income is relatively constant across age groups, with a slight increase for older children (see Figure 1.4). Children of high-income have a predicted health status closer to 0 (good health). We obtain similar differences when we add parents' health; this is also the case for the de Oliveira model. We also estimate linear probability models, which provide results similar to the probit model (not shown).

Furthermore, we try a different binary health measure, where children in excellent, very good and good health are classified as being in 'good' health, while children in fair and poor health were classified as being in 'poor' health. We find that the differences for predicted health status between high- and low-income children are quite small, as there are very few children reported to have fair or poor health in our sample.

We also perform some sensitivity analyses around our model specification. Our results are robust to the inclusion of neighbourhood characteristics[23], mother's drinking habits and the PMK's depression score. Of these, only the last variable has a

[22]Children in good health are those whose PMK-reported health status is excellent or very good in the original classification, while children in poor health are those whose PMK-reported health status is good, fair or poor.

[23]This set of variables includes the log of average income, the average family size, the percentage of two-parents families and the percentage of the population with less than high school education measured at the neighbourhood (enumeration area) level.

significant impact on the rating of the child's health – the less depressed the PMK, the healthier the child.

Finally, when we extend C&S's (2003) analysis to include all five available cycles of the NLSCY, we find that their general conclusions hold. The income coefficients remain significant and are quite similar in magnitude to those found previously by the authors. Furthermore, the increasing gradient with age remains. For the extended models (C&S, 2003 model with parent's health included, and the de Oliveira specification), we also find that our conclusions generally hold; however, we find slight changes in the income coefficients. The income coefficients are increasingly negative until ages 9-12, much like what the authors found. However, as we move from age group 9-12 to age group 13-15, the income coefficient becomes less negative; this pattern holds for both extensions. Moreover, when plotting the income coefficients by age groups we find a u-shape, much like the findings of A. Currie et al. (2006). This suggests that while there is an increasing gradient for younger ages, the pattern is reversed as we move to the older age group, suggesting that the income-health gradient is not increasing with age.

1.5.3 Results from 'Longitudinal' Models

Estimates of equation 1.2 are presented in table 1.9. To understand why the differences occur for high- and low-income children, C&S (2003) test the two hypotheses mentioned beforehand. By distinguishing between past and recent shocks, one can assess whether the differential effects of health shocks by income level persist over time or, whether given enough time, high- and low-income respond similarly to these shocks. The key variables used to understand these mechanisms are the two chronic condition dummies (presence of a chronic condition in 1994 and 1998) interacted with the log of household income.

If the interaction term between chronic condition in 1994 and income is statistically significant, then income affects the extent to which a past health shock impacts a child's health today. In other words, the long-term effects of health shocks differ by household income. However, if the variable is not statistically significant then one can conclude that both rich and poor children suffer long-term negative consequences from health shocks and, thus recuperate from these at similar rates. On the other hand, if the presence of a chronic condition in 1998 interacted with income is statistically significant, we can conclude that low-income children are less able to deal with newly arrived health shocks, and so forth. The interpretation of both variables provides insight to why high- and low-income children differ with regard to their health status.

C&S (2003) conclude that although both rich and poor children appear to suffer long-term negative consequences from chronic conditions, low-income children are harder hit harder by chronic conditions than high-income children. It should be noted that the original results from their work are based on an erroneous sample. This is due to a coding error of the health status variable into the binary measure - children with missing health status were coded as being in excellent or very good health[24]. We have re-estimated these models while taking this into account; this

[24]This error occurs only in the specification of their longitudinal model in which the dependent

provides us with slightly different results from those found previously (see original table).

One of the authors' findings was that the interaction terms in their models were not significant, which is quite important for the conclusions they reached. However with the correct samples, the interaction terms are now all significant[25]. For example, the coefficient on the interaction variable between income and chronic condition in 1994 is significant at the 10% level. This suggests that there is weak evidence that long-term effects of these shocks do not differ by income. Thus, children from both rich and poor families appear to suffer long-term negative consequences from chronic conditions, implying similar rates of recovery from health shocks. We also estimate the models found in Currie and Stabile (2002), where they test for the impact of a new current chronic condition with income (see table 1.10). Here the interaction term is significant at the 5% level, which means that low-income children are less able to deal with newly arrived health shocks, and thus hit harder by these.

We also consider both finer and broader measures of health shocks. Our finer measure of chronic conditions is asthma. Our results provide evidence that high- and low-income children are hit by asthma shocks in the same manner (long-term effects of asthma do not differ by income) but recuperate at different rates, with high-income children recuperating more quickly than low-income children. Different results are obtained when we analyse our broader measure of health shocks, chronic conditions and

variable is poor health; it does not occur in the cross-sectional model, which is the basis for the estimation of the income-health gradient.

[25]Although the level of statistical significance of the interaction terms change, the direct effects do not.

episodes of hospitalisation. The results suggest that both mechanisms are important: the long-term effects of chronic conditions and episodes of hospitalisation differ by income level and high-income children recuperate at a quicker rate than low-income children. These new findings suggest that the C&S (2003) model is not robust to sample changes.

Link and Condliffe (2008) also examined this issue using longitudinal data, but for American children. They found some evidence that the long-term effect of asthma impacts low-income children harder than their high-income counterparts, in line with C&S's (2003) findings. However, Link and Condliffe (2008) also found that low-income children respond differently to an episode of asthma when compared to children from high-income families. Similar results were found for the broader measure of health shocks.

We propose a different model to explain the health differences between rich and poor children. Estimates of equation 1.2 for the de Oliveira model are presented in table 9. Most of the previous results hold for this model, namely the impact of average household income as well as mother's education. However, slight changes in the significance level of the interaction terms provide different conclusions (see tables 1.11 and 1.12). For chronic conditions, the estimates suggest that long-term effects of these shocks do not differ by income level. However, low-income children are hit harder by chronic conditions than their high-income counterparts; this is in line with C&S's (2003) original findings. Furthermore, the results suggest that both high- and low-income children appear to suffer long-term negative consequences from asthma and that these children recuperate at different rates from these shocks. Finally, for our broader health measure, our results provide weak evidence that long-term effects of these shocks do not differ by income level.

Given these results, we conclude that the overall differences in health between high- and low-income children can be attributed to the fact that the former are affected by more chronic conditions than the latter. This conclusion does not hold for a finer measure of health shocks, such as asthma, while it does, albeit weakly, for our broader measure. We believe this aspect of the analysis requires further investigation.

1.6 Discussion

The main objective of this paper is to test the robustness of C&S's (2003) findings within the Canadian context. More specifically, we are interested in understanding whether, employing a different model specification, the income-health gradient in childhood remains; how it changes with children's age; and, the potential underlying mechanisms of this relationship. C&S (2003) find an income-health gradient much like Case et al. (2002) – the income coefficients in their model become more negative with each age group. In other words, the authors find an increasing income-health gradient — as children age, the health gap between high- and low-income children increases.

However, the authors did not account for parental health in their model; when mother's health and/or father's health are included, the conclusions change. First, the income coefficients decrease in size, i.e., they are less negative. By including parental health status, we eliminate the health impact previously captured indirectly by household income. Second, for children older than four, the income coefficients do not become more negative with age, but rather remain relatively constant, leading to a constant gradient with age. Similar results are found (with a slight decrease of the coefficient sizes) for the de Oliveira model. Thus, parents' health is a key factor in explaining the difference between high- and low-income children.

With regard to the underlying mechanisms, we find that low-income children generally are hit by more health shocks (namely chronic conditions and episodes of hospitalisation) than high-income children, contributing to the differences between these two groups.

Our main finding concerns how the trajectory of the childhood gradient over time differs from what has been documented in the literature. Income is only one of the family characteristics associated with children's health status; parental education and health are also important factors. We include controls for parental health in our model as we believe that the health of parents has an important role in explaining their children's health status. Children whose parents report to be in excellent or good health are more likely to be in good health themselves[26]. Parents in poor health are likely to have reduced income producing capacity and failure to account for parents' health in the models could result in attributing the effect of these omitted variables to household income. If this is the case, the association with current income may simply be picking up the association between poor parental health and child health

[26]In my sample of children, we do not find much correlation between mother's, father's and child's health statuses.

(Case et al., 2002); furthermore, there may also be unobserved heterogeneity.

Children's health may be affected by the health status of their parents through various channels. For example, there are likely to be genetic links in health between parents and children as children may inherit their parents' genetic predisposition for illness. Also, poor parental health might directly affect child health through a less healthy uterine environment or lower quality care. Other research finds that children whose parents have specific health behaviours, such as smoking or exercising, are more likely to have similar health (Case and Paxson, 2002). Case and Paxson (2002) focus on three specific health-related behaviours and examine their impact on children's health. The authors focus on whether a child wears a seat belt most or all of the time, whether someone in the household smokes and finally whether the child has a regular bedtime. They find that these health-related behaviours have an important impact on children's health status. Finally, parents and children may be affected by common unobservable family characteristics and environmental factors, which may lead to a correlation between their health.

The increasing gradient found by C&S (2003) disappears when we include parents' health in the model. Moreover, the impact of parents' health on children's health increases with age. An interesting question is why this is the case. One possible explanation is that family genetics are more likely to manifest themselves as diseases and illnesses later in childhood, rather than in the earlier years.

Another reason may be related to common but unmeasured environmental factors, to which both parents and children are exposed. As children become older, they become increasingly exposed to these parental 'externalities', both directly and indirectly.

Finally, as mentioned, parents may affect children's health status through health-related behaviours. Bricker et al. (2003) find that parental smoking cessation is associated with reduced risk of their children's daily smoking. As children become older, they are more likely to adopt their parents' health behaviours, and thus be influenced by these in domains such as their health status and/or educational attainment. Although our model does not predict parents' health behaviours to have a significant impact on children's health, we feel that that this variable may impact children's health via parental health. Nonetheless, this trend is likely to lose importance in adolescence as family characteristics tend to have a smaller impact on the individual; this point merits further research.

Our study presents some interesting findings, namely concerning the role of parental health in our models. Case et al. (2002) find evidence of large effects of parents' health on children's health – we confirm these results. Moreover, we find that mother's health is more strongly related to children's health than father's health; this is in line with the existing evidence. Similarly to Propper et al. (2007), we also find a strong relationship between current maternal mental health and child health.

An interesting finding is the decrease in the magnitude of the income coefficients with the inclusion of parents' health. We find that the inclusion of mother's and father's health does not completely eliminate the impact of income on children's health, contrary to Propper et al.'s (2007) findings. Furthermore, we find that some of the reduction in the income effect is due to the inclusion of a control variable for the state of repairs of the home, which may be a proxy for SES.

Some of the limitations we have encountered in our work are mainly related to our data. The lack of information on family wealth (financial and human) may be a possible deficiency in our analyses as ideally this variable (or "permanent" income, as a proxy for it) would be preferred to household income. As well, one could argue that the use of the standard ordered probit model may not be the most appropriate model to analyse an ordered dependent variable and, thus, suggest, for example, the use of the generalised ordered probit model (Boes and Winkelmann, 2006). Other authors argue that parametric models impose far too rigid assumptions to understand certain phenomena, such as health status. Li and Racine (2007), among others, have suggested the use of more flexible estimation techniques such as nonparametric models; this aspect requires further research.

The main goal of this work is to obtain a better understanding of what factors explain the income-health gradient for Canadian children. We found that parents' health status has an important role in explaining the income-health gradient, as well as other household characteristics such as the physical state of a home. Healthier parents are more likely to have healthier children, since they usually possess the means (through their educational attainment and income) to provide their children with healthier meals, better homes and, ultimately, better health care. Similarly to Propper et al. (2007), our results provide evidence that parental health has a stronger impact on child health than parents' health-related behaviours. C&S (2003) look into the reasons why low-income children have poorer health. Our results provide some evidence that low-income children may be more subject to health shocks compared to high-income children. This result calls for policies that can address the higher arrival of health shocks experienced by low-income children. Policies designed to improve children's health must account for why health and income are related. While income, health insurance coverage and advances in medical treatment may be important determinants of children's health, they are not the only ones. Dollars are not by themselves antidotes for illness. Improving children's health also calls for a broader set of policies that target parents' health status.

There is growing evidence that economic circumstances during childhood matter for later life outcomes. Future research should investigate the income-health gradient from childhood to early adulthood to see how it evolves over time with each stage. An analysis of this sort with Canadian data will only be possible once more cycles of the NLSCY are available. With additional years of data, it will be possible to follow children till the age 25 and, assess how childhood experiences affect early adulthood outcomes.

1.7 Conclusion

In this study, we have reviewed the existing literature on the income gradient in children's health, while shedding new light on the income-health gradient for Canadian children. Our analysis is motivated by the work of Case et al. (2002) and C&S (2003). These authors find that the impact of income becomes increasingly more important as children age, suggesting the existence of a growing gap between high- and low-income children with respect to health status.

Our analyses highlight a few interesting results worth noting. Adding mother's and/or father's health in C&S's (2003) model changes the main results. First, the income coefficients decrease in magnitude (they are less negative). Second, for children older than four, the income coefficients do not become more negative with age, as we have a flat gradient. Furthermore, we uncover some interesting results alongside the change in the income coefficients. We find that higher levels of maternal education have a greater impact on children's health status, unlike father's education, which is usually not significant. Being the first born child and a boy translates into better physical health, though the impact of these characteristics diminishes with age. We also find that the state of the dwelling in which a child lives has a significant impact on his/her health. Concerning the underlying mechanisms of the income-health gradient, we find some evidence that the differences between high- and low-income children can be explained in part by the fact that the latter are subject to more bad health shocks than the former, as C&S (2003) initially found.

Some authors have argued that publicly funded health care may have a protective effect on the health of children. However, evidence suggests that the health care system may play a secondary role in explaining children's health. We provide new evidence that parents' health status play an important role in explaining children's health status, rather than the health care system. Parents, not doctors, are children's primary gatekeepers. This reiterates the idea that the intergenerational transmission mechanism from parents to children is through health as healthier children have better outcomes in adulthood.

Future work will focus on the application of nonparametric methods to the problem discussed above, in effort to understand how these methods could improve the estimation of our models. We are also interested in whether our main conclusions change with the use of these methods. As mentioned, there has been substantial work on the income-health gradient in children's physical health. However, mental health conditions have a stronger impact on child outcomes than physical health conditions (Currie and Stabile, 2006); very little research has focused on the income-health gradient in children's mental health. There may be potential in pursuing this topic to understand if and how family income impacts children's mental health with age.

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Table 1.1: Studies that use the Case et al. (2002) Framework to Investigate the Income Gradient in Children's Physical Health

Study	**Country**	**Dependent Variable: Reported Health Status (subjective health measure)**	**Age Groups**	**Income-Health Gradient**	**Protective Effect of Income**	**Publication Status**
Case et al. (2002)	US	1 – excellent 2 – very good 3 – good 4 – fair 5 – poor	0 – 3 4 – 8 9 – 12 13 – 17	Yes – all age groups	Increases with age	American Economic Review
Currie J. and Stabile (2003)	Canada	1 – excellent 2 – very good 3 – good 4 – fair 5 – poor	0 – 3 4 – 8 9 – 12 13 – 15	Yes – all age groups	Increases with age	American Economic Review
Currie A. et al. (2006)	England	1 – very good 2 – good 3 – fair 4 – bad or very bad	0 – 3 4 – 8 9 – 12 13 – 15	Yes – all age groups	No clear pattern with age (however, generally decreasing with age)	Journal of Health Economics
Link and Condliffe (2008)	US	1 – excellent 2 – very good 3 – good 4 – fair 5 – poor	0 – 3 4 – 8 9 – 12 13 – 17	Yes – all age groups	Increases with age	American Economic Review
Doyle et al. (2007)	England	1 – very good 2 – good 3 – fair 4 – bad or very bad	0 – 3 4 – 8 9 – 12 13 – 15	Yes – but not for 0 – 3	No clear pattern with age	Under submission

Table 1.2: Other Studies of the Income Gradient in Children's Physical Health

Study	Country	Dependent Variable: Health Status (subjective and/or objective health measure)	Age Groups	Income-Health Gradient	Protective Effect of Income	Publication Status
Currie A. et al. (2006)	England	Various objective health measures	0 – 15	No	Not Applicable	Journal of Health Economics
Propper et al. (2007)	England	Various health measures (subjective and objective)	0 – 81 months	Yes	Constant with age	Health Economics
Nahum (2006)	Sweden	Various objective health measures	0 – 15 3 – 15 4 – 15	No	Not Applicable	Doctoral Dissertation, Uppsala University
Chen, Martin and Matthews (2006)	US	1 - excellent 2 – very good 3 – good 4 – fair 5 – poor Dichotomized: 1 – fair and poor 0 – otherwise	0 – 18	Yes	Constant with age	Social Science and Medicine
Case, Paxson and Vogl (2007)	US	1 – excellent 2 – very good 3 – good 4 – fair 5 – poor Dichotomized: 1 – fair and poor 0 – otherwise	0 – 18	Yes	Increases with age	Social Science and Medicine

Table 1.3: Means of Variables used in Currie and Stabile (2003)

	Cycle 1	**Cycle 2**	**Cycle 3**
Age	4.93	6.91	8.85
	(3.55)	(3.55)	(3.55)
Household income (CAN dollars)	50,330	50,538	57,169
	(33,178)	(33,972)	(39,128)
PMK female (* 100 in percent)	0.93	0.92	0.93
	(0.26)	(0.27)	(0.25)
Two-parent family (* 100 in percent)	0.86	0.85	0.83
	(0.34)	(0.36)	(0.38)
Mom more than high school (* 100 in percent)	0.58	0.58	0.58
	(0.49)	(0.49)	(0.49)
Household size	4.41	4.21	4.25
	(1.11)	(1.09)	(1.09)
Mom age at birth	27.68	27.68	27.68
	(4.85)	(4.85)	(4.85)
Poor health (* 100 in percent)	0.12	0.12	0.13
	(0.33)	(0.33)	(0.33)
Asthma (* 100 in percent)	0.11	0.14	0.14
	(0.31)	(0.34)	(0.25)
Activity limitation (* 100 in percent)	0.03	0.04	0.04
	(0.18)	(0.18)	(0.21)
GP visits in past year	2.78	2.06	1.76
	(4.25)	(3.14)	(2.90)
Hospitalization (* 100 in percent)	0.07	0.05	0.04
	(0.26)	(0.21)	(0.18)
Chronic condition (* 100 in percent)	0.26	0.31	0.32
	(0.44)	(0.46)	(0.47)
Number of observations	14,162	14,162	14,162

Note: Standard deviations are in parentheses.

Source: Currie and Stabile (2003)

Table 1.4: The Gradient in the United States and Canada

	Health Status Ordered Probits (1=excellent, ..., 5=poor)							
	Case et al. (2002)				Currie and Stabile (2003)			
Age Groups	**0-3**	**4-8**	**9-12**	**13-17**	**0-3**	**4-8**	**9-12**	**13-15**
Number of observations	51,448	54,067	64,746	59,069	8,961	17,260	10,446	3,507
Without mother's education								
Log of income	-0.183**	-0.244**	-0.286**	-0.323**	-0.151**	-0.216**	-0.259**	-0.272**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.026)	(0.019)	(0.024)	(0.040)
With mother's education								
Log of income	-0.114**	-0.156**	-0.187**	-0.218**	-0.132**	-0.182**	-0.215**	-0.254**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.027)	(0.020)	(0.025)	(0.041)
Mom's education = 12 years	-0.136**	-0.169**	-0.170**	-0.170**				
	(0.018)	(0.018)	(0.017)	(0.017)				
Mom's education > 12 years	-0.244**	-0.322**	-0.336**	-0.319**				
	(0.021)	(0.020)	(0.019)	(0.019)				
Mom more than high school					-0.073**	-0.135**	-0.163**	-0.067
					(0.031)	(0.022)	(0.028)	(0.046)

** Significant at the 5% level.

For details on model specifications, see Case et al. (2002) and Currie and Stabile (2003).

Table 1.5: The Gradient in Canada – Currie and Stabile's Model with Parents' Health Status (without mother's education)

	Health Status Ordered Probits (1=excellent, ..., 5=poor)			
	Currie and Stabile's Model with Parents' Health			
Age Groups	**0-3**	**4-8**	**9-12**	**13-15**
Number of observations	7,751	14,632	8,879	2,976
Without mother's education				
Log of income	-0.077**	-0.144**	-0.149**	-0.144**
	(0.028)	(0.021)	(0.027)	(0.045)
Age 1 DV	0.296**			
	(0.047)			
Age 2 DV	0.189**			
	(0.046)			
Age 3 DV	0.248**			
	(0.050)			
Age 4 DV		-0.062**		
		(0.029)		
Age 5 DV		0.000		
		(0.031)		
Age 6 DV		0.054*		
		(0.028)		
Age 7 DV		0.008		
		(0.033)		
Age 9 DV			0.055*	
			(0.030)	
Age 10 DV			-0.005	
			(0.034)	
Age 12 DV			-0.046	
			(0.039)	
Age 13 DV				-0.091
				(0.063)
Age 14 DV				-0.114*
				(0.060)

The Gradient in Canada – Currie and Stabile's Model with Parents' Health Status (without mother's education) (cont)

Year 96 DV	0.043	-0.018	-0.029	-0.186**
	(0.035)	(0.023)	(0.030)	(0.063)
Year 98 DV		0.074**	0.128**	
		(0.024)	(0.034)	
Ln family size	0.208**	-0.068	0.019	0.004
	(0.070)	(0.054)	(0.071)	(0.112)
Male	0.141**	0.057**	0.048*	-0.036
	(0.030)	(0.022)	(0.029)	(0.047)
PMK - not bio mom		0.717	0.810**	
		(0.650)	(0.198)	
PMK female	0.098*	0.123**	0.096*	-0.137
	(0.057)	(0.044)	(0.052)	(0.100)
Two parent family dummy	0.366	0.125	-0.197	-0.028
	(0.296)	(0.225)	(0.195)	(0.203)
Mom's age at child's birth	-0.007**	0.000	0.000	-0.011**
	(0.003)	(0.002)	(0.003)	(0.005)
Income imputed dummy	0.094**	0.072**	-0.006	0.069
	(0.042)	(0.036)	(0.047)	(0.098)
Poor health mom	0.445**	0.527**	0.558**	0.511**
	(0.036)	(0.025)	(0.031)	(0.052)
Poor health dad	0.263**	0.308**	0.373**	0.413**
	(0.035)	(0.024)	(0.031)	(0.049)
Pseudo - R^2	0.033	0.04	0.05	0.055

* Significant at the 10% level
** Significant at the 5% level
Observations were clustered by child ID.
Standard errors are shown in brackets.

Table 1.6: The Gradient in Canada – Currie and Stabile's Model with Parents' Health Status (with mother's education)

	Health Status Ordered Probits (1=excellent, ..., 5=poor)			
	Currie and Stabile's Model with Parents' Health			
Age Groups	**0-3**	**4-8**	**9-12**	**13-15**
Number of observations	7,751	14,632	8,879	2,976
With mother's education				
Log of income	-0.075**	-0.119**	-0.127**	-0.142**
	(0.029)	(0.022)	(0.028)	(0.047)
Mother more than high school educ.	-0.010	-0.103**	-0.090**	-0.007
	(0.034)	(0.024)	(0.030)	(0.051)
Age 1 DV	0.296**			
	(0.047)			
Age 2 DV	0.189**			
	(0.046)			
Age 3 DV	0.248**			
	(0.050)			
Age 4 DV		-0.056*		
		(0.029)		
Age 5 DV		0.005		
		(0.031)		
Age 6 DV		0.057**		
		(0.028)		
Age 7 DV		0.009		
		(0.033)		
Age 9 DV			0.056*	
			(0.030)	
Age 10 DV			-0.004	
			(0.034)	
Age 12 DV			-0.045	
			(0.039)	
Age 13 DV				-0.091
				(0.063)

The Gradient in Canada – Currie and Stabile's Model with Parents' Health Status (with mother's education) (cont)

Age 14 DV				-0.114*
				(0.060)
Year 96 DV	0.043	-0.015	-0.027	-0.185**
	(0.035)	(0.023)	(0.030)	(0.063)
Year 98 DV		0.077**	0.129**	
		(0.024)	(0.034)	
Ln family size	0.206**	-0.078	0.014	0.004
	(0.070)	(0.054)	(0.071)	(0.112)
Male	0.141**	0.058*	0.048*	-0.036
	(0.030)	(0.022)	(0.029)	(0.047)
PMK - not bio mom		0.695	0.772**	
		(0.647)	(0.197)	
PMK female	0.098*	0.125**	0.091*	-0.137
	(0.057)	(0.044)	(0.052)	(0.099)
Two parent family dummy	0.365	0.108	-0.197	-0.029
	(0.296)	(0.226)	(0.193)	(0.203)
Mom's age at child's birth	-0.007**	0.002	0.001	-0.011**
	(0.004)	(0.002)	(0.003)	(0.005)
Income imputed dummy	0.093**	0.067*	-0.010	0.068
	(0.042)	(0.036)	(0.047)	(0.098)
Poor health mom	0.444**	0.521**	0.550**	0.511**
	(0.036)	(0.025)	(0.031)	(0.053)
Poor health dad	0.263**	0.307**	0.371**	0.413**
	(0.035)	(0.024)	(0.031)	(0.049)
Pseudo - R^2	0.033	0.04	0.05	0.055

* Significant at the 10% level
** Significant at the 5% level
Observations were clustered by child ID.
Standard errors are shown in brackets.

Table 1.7: The Gradient in Canada – de Oliveira Model (without parents' education)

	Health Status Ordered Probits (1=excellent, ..., 5=poor)			
	de Oliveira Model			
Age Groups	**0-3**	**4-8**	**9-12**	**13-15**
Number of observations	7,659	14,264	8,632	2,871
Without parents' education				
Log of income	-0.056	- 0.134**	- 0.143**	- 0.121**
	(0.029)	(0.022)	(0.027)	(0.046)
Age 1 DV	0.305**			
	(0.047)			
Age 2 DV	0.220**			
	(0.047)			
Age 3 DV	0.286**			
	(0.050)			
Age 4 DV		-0.078**		
		(0.032)		
Age 5 DV		-0.012		
		(0.029)		
Age 6 DV		0.038		
		(0.032)		
Age 7 DV		0.015		
		(0.034)		
Age 9 DV			0.109**	
			(0.041)	
Age 10 DV			0.046	
			(0.034)	
Age 11 DV			0.062	
			(0.039)	
Age 13 DV				-0.094
				(0.064)
Age 14 DV				-0.132**
				(0.061)

The Gradient in Canada – de Oliveira Model (without parents' education) (cont)

Year 96 DV	0.028	-0.017	-0.026	-0.189**
	(0.035)	(0.023)	(0.030)	(0.064)
Year 98 DV		0.075**	0.137**	
		(0.024)	(0.034)	
First-born DV	- 0.206**	- 0.082**	- 0.088**	0.042**
	(0.040)	(0.026)	(0.033)	(0.055)
White DV	-0.010	-0.016	-0.045	0.000
	(0.039)	(0.029)	(0.037)	(0.062)
Ln family size	-0.091	-0.161**	-0.080	0.023
	(0.089)	(0.063)	(0.079)	(0.125)
Male	0.137**	0.059**	0.048*	-0.032
	(0.030)	(0.023)	(0.029)	(0.048)
PMK female	0.084	0.124**	0.086	-0.129
	(0.057)	(0.044)	(0.053)	(0.103)
Two parent family dummy	0.304	-0.01	-0.253	-0.043
	(0.300)	(0.249)	(0.196)	(0.215)
Mom's age at child's birth	-0.010**	-0.001	-0.002	-0.010*
	(0.004)	(0.003)	(0.004)	(0.006)
Poor health - mom	0.422**	0.516**	0.553**	0.514**
	(0.036)	(0.025)	(0.032)	(0.054)
Poor health - dad	0.273**	0.302**	0.366**	0.394**
	(0.036)	(0.025)	(0.031)	(0.051)
Smoking habits - mom	0.042	0.092**	0.018	0.038
	(0.037)	(0.027)	(0.034)	(0.058)
Smoking habits - dad	0.000	-0.012	-0.005	-0.008
	(0.035)	(0.026)	(0.032)	(0.054)
House - repairs	0.110**	0.091**	0.112**	0.197**
	(0.033)	(0.024)	(0.031)	(0.052)
Pseudo - R^2	0.036	0.042	0.051	0.058

* Significant at the 10% level
** Significant at the 5% level
Observations were clustered by child ID.
Standard errors are shown in brackets.

Table 1.8: The Gradient in Canada – de Oliveira Model (with parents' education)

	Health Status Ordered Probits (1=excellent, , 5=poor)			
	de Oliveira Model			
Age Groups	**0-3**	**4-8**	**9-12**	**13-15**
Number of observations	7,659	14,264	8,632	2,871
With parents' education				
Log of income	-0.042	- 0.091**	- 0.091**	- 0.101**
	(0.031)	(0.023)	(0.030)	(0.051)
Mother's education				
Secondary school graduate	-0.085	- 0.081**	-0.065	-0.098
	(0.053)	(0.037)	(0.044)	(0.070)
Beyond high school	-0.024	- 0.115**	- 0.091**	-0.040
	(0.048)	(0.034)	(0.041)	(0.067)
College or university	-0.040	-0.177**	- 0.245**	-0.356**
	(0.064)	(0.048)	(0.065)	(0.111)
Father's education				
Secondary school graduate	-0.083*	-0.015	-0.02	0.078
	(0.048)	(0.035)	(0.043)	(0.073)
Beyond high school	-0.063	-0.048	0.007	0.056
	(0.042)	(0.030)	(0.038)	(0.063)
College or university	-0.089	-0.071	-0.082	0.155*
	(0.057)	(0.043)	(0.056)	(0.094)
Age 1 DV	0.304**			
	(0.047)			
Age 2 DV	0.221**			
	(0.047)			
Age 3 DV	0.287**			
	(0.050)			
Age 4 DV		-0.052*		
		(0.030)		
Age 5 DV		0.010		
		(0.032)		
Age 6 DV		0.059**		
		(0.028)		

The Gradient in Canada – de Oliveira Model (with parents' education) (cont)

Age 7 DV		0.018		
		(0.034)		
Age 9 DV			0.052*	
			(0.031)	
Age 10 DV			0.013	
			(0.035)	
Age 11 DV			0.058	
			(0.039)	
Age 13 DV				-0.100
				(0.064)
Age 14 DV				-0.135**
				(0.061)
Year 96 DV	0.028	-0.014	-0.025	-0.184**
	(0.035)	(0.023)	(0.030)	(0.064)
Year 98 DV		0.078**	0.134**	
		(0.024)	(0.035)	
First-born DV	- 0.206**	- 0.068**	- 0.074**	0.050**
	(0.040)	(0.027)	(0.034)	(0.055)
White DV	-0.009	-0.016	-0.052	-0.002
	(0.039)	(0.029)	(0.037)	(0.062)
Ln family size	-0.103	-0.163	-0.074	0.032
	(0.089)	(0.063)	(0.079)	(0.125)
Male	0.139**	0.060**	0.048*	-0.039
	(0.030)	(0.023)	(0.029)	(0.048)
PMK female	0.076	0.117**	0.084	-0.115
	(0.057)	(0.045)	(0.053)	(0.103)
Two parent family dummy	0.309	-0.029	-0.252	-0.057
	(0.297)	(0.249)	(0.192)	(0.214)
Mom's age at child's birth	-0.009**	0.002	0.001	-0.007
	(0.003)	(0.003)	(0.004)	(0.006)
Poor health - mom	0.417**	0.508**	0.543**	0.514**
	(0.036)	(0.025)	(0.032)	(0.054)
Poor health - dad	0.269**	0.297**	0.361**	0.397**
	(0.036)	(0.025)	(0.031)	(0.051)

The Gradient in Canada – de Oliveira Model (with parents' education) (cont)

Smoking habits - mom	0.035	0.069**	-0.004	0.026
	(0.037)	(0.028)	(0.035)	(0.059)
Smoking habits - dad	-0.014	-0.027	-0.015	-0.007
	(0.035)	(0.026)	(0.033)	(0.055)
House - repairs	0.105**	0.090**	0.112**	0.200**
	(0.033)	(0.024)	(0.031)	(0.052)
Pseudo - R^2	0.037	0.043	0.053	0.061

* Significant at the 10% level
** Significant at the 5% level
Observations were clustered by child ID.
Standard errors are shown in brackets.

Table 1.9: Effects of Earlier Health Conditions on Poor Health Today – Currie and Stabile's model

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Chronic condition in 1994	0.116** (0.008)	0.372** (0.149)	–	–	–	–
Asthma in 1994	–	–	0.149** (0.013)	0.655** (0.229)	–	–
Chronic condition or hospitalization in 1994	–	–	–	–	0.107** (0.007)	0.386** (0.140)
Log of average income	-0.062** (0.007)	-0.055** (0.007)	-0.063** (0.007)	-0.058** (0.007)	-0.060** (0.007)	-0.053** (0.007)
Mom more than high school	-0.030** (0.007)	-0.030** (0.007)	-0.030** (0.007)	-0.030** (0.007)	-0.030** (0.007)	-0.030** (0.007)
Interactions						
Log of average income * Chronic condition in 1994		-0.024* (0.014)		-0.047** (0.021)		-0.026** (0.013)
Age 1 DV	-0.003 (0.011)	-0.003 (0.011)	0.002 (0.011)	0.001 (0.011)	0.000 (0.011)	0.000 (0.011)
Age 2 DV	0.005 (0.013)	0.005 (0.013)	0.009 (0.012)	0.008 (0.012)	0.011 (0.012)	0.010 (0.012)
Age 3 DV	0.001 (0.013)	0.001 (0.013)	0.005 (0.013)	0.004 (0.013)	0.008 (0.013)	0.008 (0.013)
Age 4 DV	-0.017 (0.013)	-0.017 (0.013)	-0.012 (0.013)	-0.012 (0.013)	-0.009 (0.013)	-0.009 (0.013)
Age 5 DV	-0.006 (0.014)	-0.006 (0.014)	0.003 (0.014)	0.004 (0.014)	0.002 (0.014)	0.002 (0.014)
Age 6 DV	-0.017 (0.014)	-0.018 (0.014)	-0.007 (0.014)	-0.007 (0.014)	-0.008 (0.014)	-0.008 (0.014)
Age 7 DV	-0.036** (0.014)	- 0.036** (0.014)	-0.025* (0.014)	-0.025* (0.014)	-0.027** (0.014)	-0.028** (0.014)
Age 8 DV	-0.007 (0.014)	-0.007 (0.014)	0.005 (0.014)	0.004 (0.014)	0.002 (0.014)	0.001 (0.014)

Effects of Earlier Health Conditions on Poor Health Today – Currie and Stabile's model (cont)

Age 9 DV	-0.025*	-0.026*	-0.013	-0.014	-0.016	-0.017
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age 10 DV	0.003	0.003	0.016	0.016	0.013	0.013
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Age 11 DV	0.011	0.011	0.026*	0.027*	0.020	0.020
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Ln family size	0.033**	0.033**	0.028**	0.028**	0.033**	0.033**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Male	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
PMK - not bio mom	-0.084	-0.082	-0.084	-0.081	-0.088	-0.086
	(0.083)	(0.083)	(0.094)	(0.094)	(0.086)	(0.086)
PMK female	-0.018	-0.018	-0.015	-0.015	-0.018	-0.019
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Two parent family dummy	-0.015	-0.014	-0.015	-0.014	-0.015	-0.014
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Mom's age at child's birth	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Income imputed dummy	0.024**	0.023**	0.024**	0.024**	0.023**	0.023**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Constant	0.719**	0.652**	0.737	0.683**	0.696**	0.611**
	(0.070)	(0.072)	(0.070)	(0.070)	(0.070)	(0.072)
Pseudo - R^2	0.038	0.038	0.034	0.034	0.037	0.037
Number of observations	13,107	13,107	13,107	13,107	13,107	13,107

* Significant at the 10% level
** Significant at the 5% level
Observations were clustered by family ID.
Standard errors are shown in brackets.

Table 1.10: Effects of Current Health Conditions on Poor Health Today – Currie and Stabile's model

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Chronic condition in 1998	0.147** (0.009)	0.584** (0.149)	–	–	–	–
Asthma in 1998	–	–	0.149** (0.015)	0.570* (0.296)	–	–
Chronic condition or hospitalization in 1998	–	–	–	–	0.151** (0.008)	0.540** (0.161)
Log of average income	-0.058** (0.007)	-0.050** (0.007)	-0.061** (0.007)	-0.059** (0.007)	-0.058** (0.007)	-0.050** (0.007)
Mom more than high school	-0.030** (0.007)	-0.030** (0.007)	-0.028** (0.007)	-0.028** (0.007)	-0.030** (0.007)	-0.030** (0.007)
Interactions						
Log of average income * Chronic condition in 1998		-0.041** (0.015)		-0.039 (0.028)		-0.036** (0.015)
Age 1 DV	0.01 (0.011)	0.011 (0.011)	0.01 (0.011)	0.011 (0.011)	0.01 (0.011)	0.011 (0.011)
Age 2 DV	0.013 (0.012)	0.014 (0.012)	0.02 (0.012)	0.021 (0.012)	0.014 (0.012)	0.014 (0.012)
Age 3 DV	0.013 (0.013)	0.014 (0.013)	0.02 (0.013)	0.021 (0.013)	0.012 (0.013)	0.013 (0.013)
Age 4 DV	-0.003 (0.013)	-0.003 (0.013)	0.006 (0.013)	0.006 (0.013)	-0.003 (0.013)	-0.003 (0.013)
Age 5 DV	0.016 (0.014)	0.017 (0.014)	0.024* (0.014)	0.025* (0.014)	0.018 (0.014)	0.018 (0.014)
Age 6 DV	0.005 (0.014)	0.005 (0.014)	0.017 (0.014)	0.017 (0.014)	0.007 (0.014)	0.007 (0.014)
Age 7 DV	-0.011 (0.013)	-0.01 (0.013)	0 (0.014)	0.001 (0.014)	-0.01 (0.013)	-0.009 (0.013)
Age 8 DV	0.016 (0.014)	0.017 (0.014)	0.027* (0.014)	0.027* (0.014)	0.018 (0.014)	0.018 (0.014)

Effects of Current Health Conditions on Poor Health Today – Currie and Stabile's model (cont)

Age 9 DV	0.002	0.002	0.012	0.013	0.003	0.004
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age 10 DV	0.032**	0.033**	0.043**	0.043**	0.034**	0.034**
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)
Age 11 DV	0.041**	0.041**	0.052**	0.052**	0.042**	0.042**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Ln family size	0.034**	0.034**	0.027*	0.027*	0.035**	0.035**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Male	-0.003	-0.003	0.002	0.003	-0.003	-0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
PMK - not bio mom	-0.066	-0.063	-0.067	-0.066	-0.075	-0.071
	(0.077)	(0.076)	(0.089)	(0.089)	(0.080)	(0.079)
PMK female	-0.012	-0.012	-0.011	-0.011	-0.011	-0.011
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Two parent family dummy	-0.017	-0.016	-0.017	-0.016	-0.016	-0.015
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Mom's age at child's birth	0.001**	0.002**	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Income imputed dummy	0.021**	0.022**	0.021**	0.021**	0.021**	0.021**
	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Constant	0.667**	0.567**	0.719	0.689**	0.659**	0.561**
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.072)
Pseudo - R^2	0.049	0.05	0.03	0.03	0.053	0.054
Number of observations	13,107	13,107	13,107	13,107	13,107	13,107

* Significant at the 10% level
** Significant at the 5% level
Observations were clustered by family ID.
Standard errors are shown in brackets.

Table 1.11: Effects of Earlier Health Conditions on Poor Health Today – de Oliveira Model

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Chronic condition in 1994	0.106** (0.008)	0.386** (0.180)	–	–	–	–
Asthma in 1994	–	–	0.139** (0.013)	0.548** (0.278)	–	–
Chronic condition or hospitalization in 1994	–	–	–	–	0.098** (0.008)	0.426** (0.170)
Log of average income	-0.041** (0.008)	- 0.035** (0.008)	-0.042** (0.008)	-0.038** (0.008)	-0.040** (0.008)	-0.031** (0.008)
Mother's education						
Sec. school grad.	-0.031** (0.012)	-0.031** (0.012)	-0.035** (0.012)	-0.035** (0.012)	-0.032** (0.012)	-0.032** (0.012)
Beyond high school	-0.036** (0.011)	-0.036** (0.011)	-0.038** (0.011)	-0.037** (0.011)	-0.037** (0.011)	-0.037** (0.011)
College or university	-0.059** (0.014)	-0.059** (0.014)	-0.061** (0.014)	-0.061** (0.014)	-0.059** (0.014)	-0.060** (0.014)
Father's education						
Sec. school grad.	-0.011 (0.011)	-0.011 (0.011)	-0.011 (0.011)	-0.011 (0.011)	-0.010 (0.011)	-0.010 (0.011)
Beyond high school	-0.010 (0.009)	-0.010 (0.009)	-0.008 (0.009)	-0.008 (0.009)	-0.009 (0.009)	-0.009 (0.009)
College or university	0.009 (0.012)	0.009 (0.012)	0.010 (0.012)	0.010 (0.0120	0.010 (0.012)	0.010 (0.012)
Interactions						
Log of average income * Chronic condition in 1994		-0.026 (0.017)		-0.038** (0.025)		-0.030* (0.016)
Age 1 DV	0.000 (0.012)	0.000 (0.012)	0.005 (0.012)	0.004 (0.011)	0.004 (0.012)	0.003 (0.012)
Age 2 DV	0.003 (0.013)	0.002 (0.013)	0.006 (0.013)	0.006 (0.013)	0.008 (0.013)	0.007 (0.013)

Effects of Earlier Health Conditions on Poor Health Today – de Oliveira Model (cont)

Age 3 DV	0.012	0.011	0.015	0.015	0.019	0.019
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)
Age 4 DV	-0.005	-0.006	-0.001	-0.001	0.002	0.001
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age 5 DV	-0.010	-0.010	0.000	0.000	-0.002	-0.002
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Age 6 DV	-0.018	-0.019	-0.009	-0.009	-0.009	-0.010
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Age 7 DV	-0.040**	-0.041**	-0.030**	-0.031**	-0.032**	-0.033**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age 8 DV	-0.013	-0.013	-0.003	-0.003	-0.005	-0.006
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Age 9 DV	- 0.030**	- 0.030**	-0.018	-0.018	-0.022	-0.022
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Age 10 DV	0.003	0.003	0.009	0.009	0.006	0.006
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Age 11 DV	0.003	0.003	0.009	0.010	0.005	0.005
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
First-born DV	-0.018**	-0.018**	-0.017**	-0.017**	-0.019**	-0.019**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
White DV	-0.001	0.000	-0.002	-0.002	-0.001	-0.001
	(0.006)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Ln family size	0.008	0.008	0.005	0.006	0.007	0.008
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Male	0.001	0.002	0.002	0.002	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
PMK female	-0.014	-0.014	-0.011	-0.011	-0.014	-0.014
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Two parent family dummy	0.011	0.011	0.011	0.011	0.007	0.007
	(0.083)	(0.084)	(0.083)	(0.083)	(0.084)	(0.084)
Mom's age at child's birth	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Effects of Earlier Health Conditions on Poor Health Today – de Oliveira Model (cont)

Poor health - mom	0.083**	0.083**	0.086**	0.086**	0.083**	0.083**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Poor health - dad	0.042**	0.042**	0.040**	0.040**	0.041**	0.041**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Smoking habits - mom	0.003	0.003	0.003	0.003	0.003	0.003
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
Smoking habits - dad	0.002	0.002	0.000	0.000	0.002	0.002
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
House - repairs	0.027**	0.027**	0.029**	0.029**	0.027**	0.027**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Constant	0.523**	0.452**	0.533**	0.490**	0.510**	0.414
	(0.123)	(0.125)	(0.123)	(0.123)	(0.123)	(0.127)
Pseudo - R^2	0.058	0.058	0.054	0.055	0.057	0.057
Number of observations	11,277	11,277	11,277	11,277	11,277	11,277

* Significant at the 10% level
** Significant at the 5% level
Observations were clustered by family ID.
Standard errors are shown in brackets.

Table 1.12: Effects of Current Health Conditions on Poor Health Today – de Oliveira Model

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Chronic condition in 1998	0.143**	0.686**	–	–	–	–
	(0.009)	(0.202)				
Asthma in 1998	–	–	0.150**	0.650*	–	–
			(0.016)	(0.356)		
Chronic condition or hospitalization in 1998	–	–	–	–	0.148**	0.697**
					(0.009)	(0.194)
Log of average income	-0.037**	-0.027**	-0.039**	-0.035**	-0.038**	-0.026**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Mother's education						
Sec. school grad.	-0.036**	-0.035**	-0.037**	-0.037**	-0.036**	-0.036**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Beyond high school	-0.038**	-0.038**	-0.037**	-0.037**	-0.039**	-0.039**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
College or university	-0.062**	-0.062**	-0.061**	-0.061**	-0.062**	-0.062**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Father's education						
Sec. school grad.	-0.013	-0.013	-0.013	-0.013	-0.013	-0.012
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Beyond high school	-0.007	-0.007	-0.009	-0.008	-0.007	-0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
College or university	0.013	0.013	0.010	0.010	0.013	0.013
	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)
Interactions						
Log of average income * Chronic condition in 1998		-0.050**		-0.046		- 0.051**
		(0.019)		(0.032)		(0.018)
Age 1 DV	0.013	0.014	0.012	0.013	0.013	0.014
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age 2 DV	0.010	0.010	0.016	0.016	0.010	0.010
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)

Effects of Current Health Conditions on Poor Health Today - de Oliveira Model (cont)

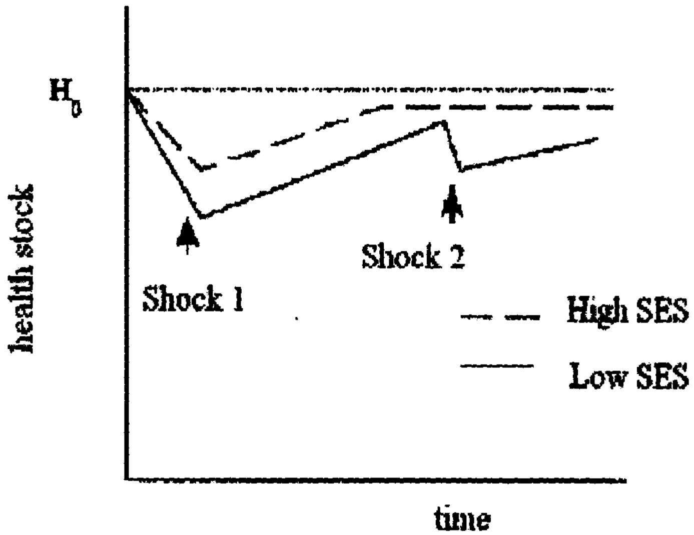
Age 3 DV	0.022	0.023	0.030	0.030	0.021	0.022
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age 4 DV	0.008	0.009	0.015	0.016	0.009	0.009
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age 5 DV	0.013	0.013	0.02	0.021	0.015	0.016
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Age 6 DV	0.004	0.004	0.015	0.015	0.006	0.006
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Age 7 DV	-0.018	-0.017	-0.007	-0.006	-0.017	-0.016
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age 8 DV	0.007	0.007	0.018	0.019	0.008	0.008
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Age 9 DV	-0.004	-0.003	0.005	0.006	-0.002	-0.002
	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)
Age 10 DV	0.025*	0.026*	0.035**	0.036**	0.026*	0.027*
	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)	(0.015)
Age 11 DV	0.024	0.024	0.035**	0.035**	0.025	0.025
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
First-born DV	-0.023**	-0.023**	-0.021**	-0.021**	-0.022**	-0.022**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
White DV	0.000	-0.001	-0.002	-0.002	-0.001	-0.001
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Ln family size	0.007	0.007	0.002	0.001	0.009	0.009
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Male	0.000	0.000	0.004	0.004	0.000	0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
PMK female	-0.001	-0.009	-0.008	-0.008	-0.009	-0.009
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Two parent family dummy	0.021	0.023	0.014	0.016	0.032	0.036
	(0.084)	(0.084)	(0.080)	(0.079)	(0.081)	(0.081)
Mom's age at child's birth	0.000	0.000	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Effects of Current Health Conditions on Poor Health Today - de Oliveira Model (cont)

Poor health - mom	0.084**	0.084**	0.085**	0.085**	0.083**	0.084**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Poor health - dad	0.040**	0.039**	0.043**	0.043**	0.040**	0.040**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Smoking habits - mom	0.004	0.004	0.004	0.004	0.004	0.004
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)
Smoking habits - dad	0.004	0.004	0.003	0.003	0.004	0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
House - repairs	0.026**	0.026**	0.029**	0.029**	0.027**	0.027**
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)
Constant	0.471**	0.349**	0.500**	0.464**	0.451**	0.316**
	(0.123)	(0.123)	(0.121)	(0.120)	(0.121)	(0.122)
Pseudo - R^2	0.07	0.071	0.053	0.053	0.075	0.076
Number of observations	11,277	11,277	11,277	11,277	11,277	11,277

* Significant at the 10% level
** Significant at the 5% level
Observations were clustered by family ID.
Standard errors are shown in brackets.

Figure 1.1: Changes in the Health Stock over Time by SES



Source: Currie and Stabile (2003)

Figure 1.2: Income Coefficients by Age Group

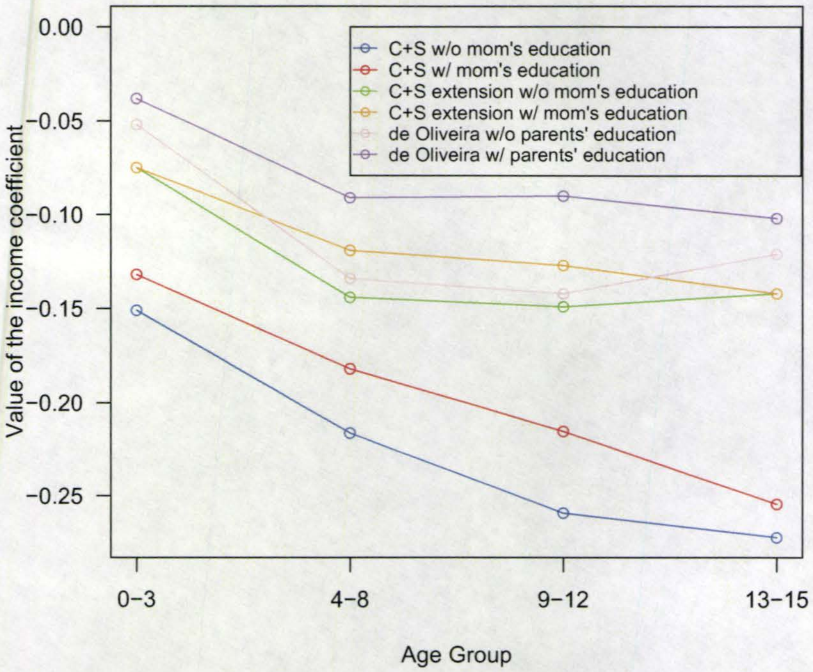


Figure 1.3: Parents' Health Coefficients by Age Group

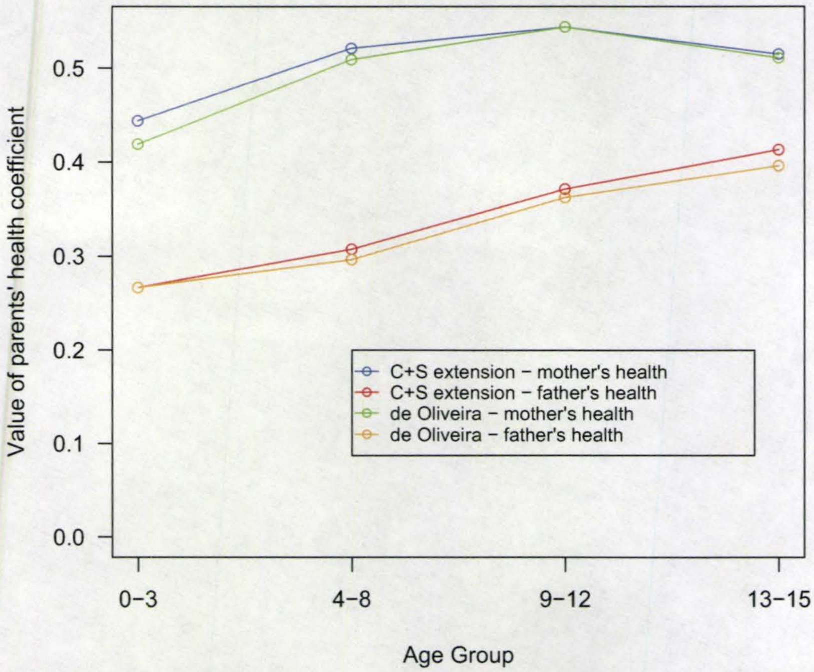
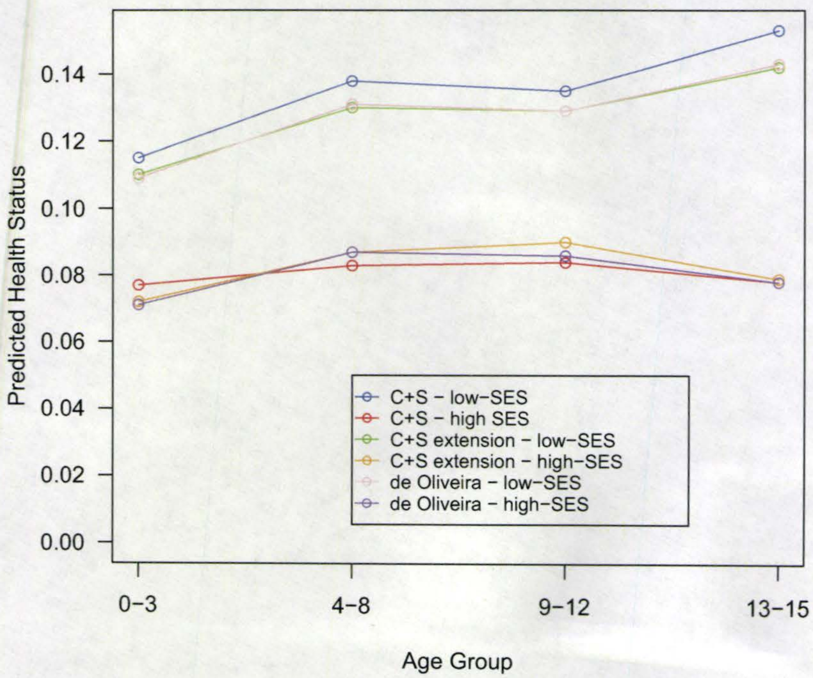


Figure 1.4: Predicted Health Status by SES and Age Group



Chapter 2

Analysing the Relationship between Child Health and Family Income: A Nonparametric Approach

2.1 Introduction

The relationship between income and health in childhood has received considerable attention in recent years. In an influential paper using American cross-sectional data, Case et al. (2002) find a positive relationship between child health and family income. Furthermore, they find that this relationship is stronger as children become older. Using the same methods (a parametric ordered probit model), Currie and Stabile (2003) estimate the relationship using Statistics Canada National Longitudinal Survey of Children and Youth (NLSCY) and find similar results. Also based on the NLSCY, using the same estimation technique, but a new model specification, in Chapter 1 we obtained quite different results. The ordered probit model, a linear index specification, performs poorly in predicting correctly a child's reported health status (see Chapter 1); this may be due to the rigidity of the model's assumptions. To overcome this problem, Li and Racine (2007), among others, have suggested the use of more flexible estimation techniques.

No study has examined the relationship between child health status and household income using nonparametric methods. These methods have the advantage of being robust to misspecification. Moreover, the use of nonparametric estimation methods has been shown to reveal important structure in the data that may not be captured by traditional parametric models.

By way of example, Li and Racine (2004a) revisit Fair's (1978) 'theory of extramarital affairs' by making use of robust nonparametric methods developed for the analysis of categorical data. Using a parametric tobit model, Fair (1978) found that infidelity, measured by the number of extramarital affairs per year, increased significantly with the number of years married. Applying a kernel estimator proposed by Hall et al. (2004), Li and Racine (2004a) find that the cross-validated smoothing parameter associated with the number of years married coincides with its upper bound indicating, contrary to the results provided by the parametric model, that the number of years married is not a relevant predictor of the number of extra-marital affairs after controlling for other covariates. Furthermore, prediction results obtained by the authors indicate that the parametric model is misspecified. In this paper, we apply this line of inquiry to the income/health relationship.

Our main objective is to understand whether a nonparametric approach can help us understand the income-health gradient in childhood. In this paper, we assess the appropriateness of our nonparametric model via three measures. First, we evaluate the improvement obtained with the use of nonparametric estimation methods in terms of the model's goodness of fit both in- and out-of-sample. To do so, we compute and compare the correct classification ratio (CCR) for both our parametric and nonparametric models. For the parametric model, we find a CCR of 58.6% in-sample and a CCR of 57.9% out-of-sample, while for our nonparametric model we find a CCR of 78.2% in-sample and a CCR of 75.8% out-of-sample. Thus, the results of our nonparametric model are not an artifact of overfitting, suggesting that this model is closer to the true data generating process. Second, we obtain an improved understanding of the determinants of child health through the use of Hall et al.'s (2004) cross-validation method, which automatically removes irrelevant predictors from the model. Third, we test whether our nonparametric model can uncover relationships in the data that may not be captured by our parametric model.

Our results show that the nonparametric model provides a 33% and 31% improvement in terms of the model's predictive power in- and out-of-sample, respectively, when compared to its parametric counterpart. Moreover, we find a constant gradient for the probability of being in either excellent or poor health.

2.2 Literature

Case et al. (2002) were the first to show that the well-known positive cross-sectional relationship between family income and health observed in adulthood also holds in childhood for American children. They find that household income is positively associated with children's health and that the strength of this relationship increases with child age, suggesting a protective effect of income on children's health status. Furthermore, Case et al. (2002) find that children's health is closely linked to long-run average family income and that the adverse health effects of lower permanent income accumulate over their lives.

Currie and Stabile (2003) also examine this relationship using Canadian data and find quite similar results – the income-health gradient increases with age for Canadian children. Moreover, the authors provide evidence that low-income children are more likely to suffer from chronic conditions when compared to children from high-income families. In Chapter 1, we revisit Currie and Stabile's (2003) paper and find that the income gradient in children's health is constant with age – that is, the difference in health between high- and low-income children does *not* increase throughout childhood.

This research all use the standard ordered probit specification to estimate their models. This specification is used to model a discrete dependent variable that takes on ordered multinomial outcomes, such as $y = 1, 2, \ldots, m$, and is commonly used in the health economics literature to examine self-assessed health status. A key assumption is that the error term is normally distributed, but other assumptions, including the single index assumption and the constant threshold assumption, can also pose serious limitations to the analysis.

There have been recent advances in the estimation of binary response models that relax the parametric assumptions of the standard ordered probit. For example, Boes and Winkelmann (2005) consider a richer class of parametric models, which allow for a more flexible analysis of marginal probability effects. They show that additional flexibility can be gained through the use of the generalised threshold model, the sequential model, and by modelling individual heterogeneity through either a random coefficients model or a finite mixture/latent class model. Nonetheless, these models continue to exhibit parametric rigidities.

An alternative approach is to recognise that a priori there is no knowledge of the underlying distribution of the error term. Nonparametric estimation addresses this concern as it makes very minimal assumptions regarding the data generating process. Unfortunately, there are very few applications of kernel-based nonparametric and semiparametric estimators in the health economics literature (Jones, 2000). Nonetheless, in recent years the use of nonparametric techniques has increased as software has become more readily available.

Although the use of nonparametric estimation is rare in the child health literature, we highlight a few studies that have made use of these techniques. While their paper employs the standard ordered probit for estimation purposes, Case et al. (2002) also make use of nonparametric techniques to analyse the conditional expectations of children's health status as a function of family income by age group. The conditional expectations are estimated using Fan's (1992) locally weighted regression smoother, which enables the data to determine the shape of the income-health function, rather than imposing a linear form. The authors find that the inverse relationship between child health and income becomes progressively more negative with age, as found for adults.

Currie and Stabile (2003) also make use of the locally weighted scatterplot smoother. They graph the distribution of poor health by age for children to analyse whether the income of the household they live in is above or below the Canadian low-income cut-off (LICO)[1]. Their findings suggest that the incidence of poor health is higher at every age for those children below the low-income cut-off. Despite the use of non-parametric techniques for graphing purposes, neither study used these methods for model estimation.

Duflo (2000) provides nonparametric evidence of the effects of the expansion of the Old Age Pension program in South Africa on child health. The objective is to understand whether the increase in household resources (through the receipt of pensions) improves child health and nutrition, and whether the gender of the recipient of the pension affects its impact. The paper looks specifically at the impact of receiving a pension on children's height as this measure reflects accumulated investments in child nutrition. Also by means of Fan's (1992) locally weighted regression, Duflo (2000) plots height and height-for-age as a function of date of birth in eligible and non-eligible households to examine the relative positions of these two curves. The results suggest that the extension of the Old Age Pension program in South Africa led to an improvement in the health and nutrition of children, especially for girls, an effect entirely due to pensions received by grandmothers.

[1]The LICO identifies individuals who are substantially worse off than the average; the composition of this measure accounts for household income, family composition and size of area of residence.

2.3 Data

We use data from Statistics Canada National Longitudinal Survey of Children and Youth (NLSCY), which follows Canadian children's development and well-being from birth to early adulthood. The NLSCY is conducted by Statistics Canada, in partnership with Human Resources and Social Development Canada (formerly Social Development Canada).

The survey is specifically designed to collect information on factors influencing a child's social, emotional and behavioural development and to monitor the impact of these factors on a child's development over time. The target population comprises the non-institutionalised civilian population (aged 0 to 11 at the time of their selection) in Canada's 10 provinces. The survey excludes children living on Indian reserves or Crown lands, residents of institutions, children of full-time members of the Canadian Armed Forces, and residents of some remote regions. The NLSCY is a probability-based sample survey, drawn from the Labour Force Survey's (LFS) sample of respondent households[2].

2.4 Methods

The term "nonparametric regression" is commonly used to refer to statistical techniques in which the functional form of the object being estimated need not be spec-

[2]For a detailed account of the NLSCY methodology, see Statistics Canada and Social Development Canada (2005) Microdata User, Statistics Canada.

ified. Thus, rather than assuming that the functional form is known, nonparametric estimation makes less restrictive assumptions such as smoothness (differentiability) and moment restrictions for the objects being studied (Li and Racine, 2007). In practice, this method uses appropriately weighted local averages to estimate functions of unknown form.

If one had knowledge of the correct specification, parametric models would, of course, perform better than their nonparametric counterparts (Li and Racine, 2007). However, in reality we seldom know the exact functional form of the object we seek to estimate. This can lead to cases where the estimated model is misspecified, which can bias the results, lead to inconsistent estimates, and produce unsound inference. Furthermore, nonparametric techniques can reveal structure in the data that may not always be captured by parametric models (see for example, Li and Racine, 2004a, discussed above).

Nonparametric models are best suited to situations in which one has little or no information about the functional form of the model being estimated, the number of covariates is small and the researcher is working with a relatively large data set. However, since nonparametric techniques generally impose fewer assumptions than their parametric counterparts, they tend to be slower to converge than parametric estimators. As a result, these methods are quite computationally intensive. The use of a computer cluster at McMaster University's Research Data Centre helped overcome this obstacle.

There are two key issues in nonparametric estimation of the type that we use here, namely the choice of a kernel function and the choice of a bandwidth (or smoothing) parameter. The kernel function provides the weight given to each observation and the smoothness of the resulting estimate, whereas the bandwidth determines the amount of local averaging used in the analyses. The weight varies with the distance between the observation and the point at which the density is being estimated. The kernel can take on a variety of forms (e.g. Epanechnikov and Gaussian) and is commonly a positive real function. In addition, kernel functions are often selected to be symmetric and unimodal density functions. In practice, it is generally the case that the precise shape of the kernel does not have much impact on the resulting estimate.

The kernel methods we employ in this paper make use of what is known in the literature as 'generalised product kernels' (see Hall, Racine and Li, 2004; Li and Racine, 2003; Li and Racine, 2004b; Li and Racine, 2007; Ouyang, Li and Racine, 2006 and Racine and Li, 2004). Generalised product kernel functions are formed by taking the product of a series of univariate kernels that are appropriate for each variable's datatype. While estimation tends to be insensitive to kernel choice, the same cannot be said about the bandwidths. Bandwidth selection is a crucial aspect of nonparametric econometrics. In our model, the selection of the bandwidths is determined by least squares cross-validation (Hall, Racine and Li, 2004).

A common problem in many models is the presence of irrelevant variables. Let's suppose that for a given vector X of explanatory variables, we wish to to estimate the conditional density of an outcome, say Y, which we define as a random variable with conditional distribution $F(y|x)$. If the j^{th} component of the X matrix is independent of Y, then that component is irrelevant in the estimation of the conditional density of y given x and, ideally, should be dropped before conducting statistical inference. By doing so, we improve both the convergence rate of the nonparametric model and the method's statistical accuracy. However, in practice it can be difficult to assess which components of X are relevant to the problem of conditional inference, and which are not.

Hall et al. (2004) suggest a version of least squares cross-validation that is suited to both choosing smoothing parameters (i.e., bandwidths) and removing irrelevant explanatory variables from the model. This data-driven method automatically determines which components of the model are relevant, and which are not, by assigning large smoothing parameters to the latter, which consequently shrinks them towards a uniform distribution of the respective marginals. Thus, this method removes irrelevant variables form the model by suppressing their contribution to the estimator variance. With regards to the relevant components, these are smoothed in the usual way; that is, cross-validation assigns smoothing parameters that are appropriate when only the relevant components are used for inference. This method of selecting the smoothing parameters is based on the principle of selecting bandwidths that minimise the integrated squared error of the resulting estimate; in other words, the difference between the difference between $\hat{g}(y|x)$ and $g(y|x)$ (see sub-section 4.2 for more details). In addition, the least squares cross-validation method is suitable for dealing with both discrete and continuous covariates.

2.4.1 Description of the Nonparametric Model

The dependent variable of our model is the child's physical health status as reported by the person most knowledgeable of the child (PMK). This information is available for children aged 0 to 15 and is measured on a 5-point Likert scale, where 1 is excellent health and 5 is poor health. Our sample is characterized by a large number of children in either excellent or very good health, 58.88% and 29.49% respectively. For the remaining health categories we have 10.44% of children in good health, 1.34% in fair health and, finally, 0.18% in poor health.

We work with a sample of children present in Cycles 1, 2 and 3 of the NLSCY, for which the surveys were done in 1994, 1996 and 1998. Although the children in our analysis belong to the longitudinal cohort, we pool all observations and treat these as cross-sectional data, in line with Currie and Stabile's (2003) and Chapter 1.

We estimate the following model using nonparametric regression techniques:

$$health_{it} = f(ln(inc)_{it}, x_{it}) + u_{it} \tag{2.1}$$

where $health_{it}$ is regressed on the log of household income, a series of child, parental and household covariates x_{it}, and an error term, u_{it}, and where the functional form of the regression is unknown. The subscript i denotes the individual child, while the subscript t represents the cycle in which the child is observed.

The key explanatory variable in our model is household income (natural logarithm). This variable is adjusted for price inflation using the Canadian Consumer

Price Index[3]. When household income is not reported, Statistics Canada imputes a value. Other socioeconomic status variables include mother's and father's education. Each parent's educational attainment was classified into one of four categories (1 - less than secondary school; 2 - secondary school graduation; 3 - beyond high school; and 4 - college or university degree (including trade)).

We also control for child, parental and household characteristics: child's age (which will be of particular importance in our analysis); dummy variables indicating the child's sex and ethnicity (white vs. non-white); the child's birth order; year effects (year dummies); family size (natural logarithm); mother's age at the birth of the child and dummy variables indicating whether the child belongs to a two-parent household; whether the PMK is female; whether the mother and father smoke and, whether the physical housing conditions in which the child lives are poor. Finally, and of particular interest, we also include dummy variables indicating whether the mother and father are in poor health; All information is reported by the PMK.

Summary statistics can be found in Table 2.1. Our sample is made up of a relatively healthy cohort of children with an average age of about 7 and roughly the same number of boys and girls. The average household income is roughly $57,620 Canadian dollars. The typical family is white, and is comprised of four people. The parents of these children are relatively healthy and educated[4].

[3]All household income values are in constant 1998 Canadian dollars.

[4]This is the same sample used in Chapter 1 for the de Oliveira model (n = 33,426). Thus, the results from our nonparametric model provide a direct comparison to the results of our parametric model.

2.4.2 Description of the Nonparametric Estimator

The nonparametric estimator employed in our analyses is a conditional probability kernel estimator. Let$f(x, y)$ and $m(x)$ denote the joint and marginal densities of (X, Y) and X, respectively, where Y is the explained variable and X the set of explanatory variables. Given that X is a mixture of continuous (x^c) and discrete (x^d) variables, let us write $x = (x^c, x^d)$. Since we do not know the values of $f(x, y)$ and $m(x)$, we use $\hat{f}$(x,y) and $\hat{m}$(x) to denote their kernel estimators and estimate the conditional probability $g(y|x) = \frac{f(x,y)}{m(x)}$ as follows:

$$\hat{g}(y|x) = \frac{\hat{f}(x, y)}{\hat{m}(x)} \tag{2.2}$$

Our estimators of $f(x, y)$ and $m(x)$ are given by

$$\hat{f}(x, y) = \frac{1}{n}\sum_{i=1}^{n} K_\gamma(x, X_i)L(y, Y_i, \lambda_0) \tag{2.3}$$

$$\hat{m}(x) = \frac{1}{n}\sum_{i=1}^{n} K_\gamma(x, X_i) \tag{2.4}$$

where λ_o is the smoothing parameter associated with Y, γ = (h,λ) the smoothing parameters for the x^c and x^d variables, and our kernel functions are given by

$$K_\gamma(x, X_i) = W_h(x^c, X_i^c)L(x^d, X_i^d, \lambda) \tag{2.5}$$

$$W_h(x^c, X_i^c) = \prod_{s=1}^{p} \frac{1}{h_s} w\left(\frac{x_s^c - X_{is}^c}{h_s}\right) \tag{2.6}$$

$$L(x^d, X_i^d, \lambda) = \prod_{s=1}^{q} \left(\frac{\lambda_s}{c_s - 1}\right)^{[N_{is}(x)]} (1-\lambda_s)^{[1-N_{is}(x)]} \tag{2.7}$$

where $N_{is}(x)$ is an indicator function that equals one when $X_{is}^d \neq x_s^d$ (zero otherwise) and $L(y, Y_i, \lambda_0) = \lambda_0^{N_i(y)}\ (1-\lambda_0)^{1-N_i(y)}$, where $N_i(y) = 1\ (Y_i \neq y)$. A second-order Gaussian kernel is used for the continuous variables; a Wang-van Ryzin kernel for the ordered discrete variables and, lastly, a Li-Racine kernel for the unordered discrete variables (see Hayfield and Racine, 2007a and 2007b; Li and Racine, 2004 and Wang and van Ryzin, 1981 for more details).

The method used to select our bandwidths is the least squares cross-validation method proposed by Hall et al. (2004), which selects bandwidths (h, λ) by minimising the weighted integrated square error (ISE) – that is, the difference between $\hat{y}$ and y.

$$ISE = \int [\hat{g}(y|x) - g(y|x)]^2 m(x) dW(x) dy \tag{2.8}$$

We use the R (R Development Core Team, 2006) package 'np' to generate the nonparametric results presented in the appendix. (For more details on this package, see Hayfield and Racine, 2007a and 2007b.)

2.5 Results

Our main objective is to understand whether a nonparametric approach can provide additional insight into the income-health gradient in childhood. First, to assess whether the nonparametric model provides an advantage over its parametric counterpart, we compute and compare the correct classification ratio (CCR) for each model. In other words, we calculate the number of times that each model correctly predicts the actual value of the dependent variable. The parametric model provides a CCR of 58.6% and 57.9% in- and out-of-sample, respectively, while the nonparametric model has a CCR of 78.2% and 75.8% in- and out-of-sample, respectively. Thus, with the nonparametric model we have a non-trivial improvement of about 30% in terms of the model's predictive power, whether it be in- or out-of-sample.

Some researchers may criticize our nonparametric model because they believe any improved fit is illusory as it may reflect an overfitting of the model. However, if two models are misspecified, clearly the one that performs better out-of-sample is to be preferred since it is the one closer to the true data generating process.

Table 2.2 reports the estimated cross-validation smoothing parameters ($\widehat{h}$ and $\widehat{\lambda}$). We remind the reader that h is the smoothing parameter for continuous variables, while λ is the smoothing parameter for discrete (ordered and unordered) variables. The "Upper Bound" column denotes the maximum value the smoothing parameters can take on[5]. We can see that the smoothing parameters for the variables 'year',

[5]For continuous variables the upper value for h is ∞, whereas for ordered discrete variables the upper value for λ is 1 and, for unordered discrete variables the upper value for λ is 0.5.

'dummy for whether the child lives in a two-parent household', 'birth order' and 'dummy for whether the house is in need of repairs' coincide with their respective upper bounds. In other words, these variables have no explanatory power and are, therefore, "smoothed out" (i.e., excluded) from the model. All other variables in the model have been smoothed in the traditional manner.

This finding is particularly interesting since in Chapter 1 we found the physical state of the home to be a strong predictor of a child's physical health status. This variable is weakly correlated with household income, parental health and parental smoking habits. Thus, the dummy variable indicating whether a home is in need of repairs is not picking up the income effect in the parametric model. We do not have a theoretical explanation as for why this variable has been dropped from our model. This result requires further understanding.

We begin by looking at the kernel estimates of the conditional probability of being in a given health state (excellent, very good, good, fair and poor) for all ages, 0 to 15. We generate the conditional probability of a child being in each health category while holding all explanatory variables constant at either their modal or median value (for dichotomous, and ordered and continuous variables, respectively).[6]

In Figure 2.1, we find that the conditional probability of being in each health category is roughly the same for all ages. More specifically, we find that there is more variability across each health category than within a given health category across all ages. At first blush, this would suggest that, ceteris paribus, the probability of a child being in a given health state is the same for all ages.

[6]See the Appendix for more details on this.

In Figure 2.2, we compare the predicted conditional probabilities of being in each health state for both our parametric and nonparametric models. We find that the parametric model yields a lower probability of a given child being in excellent health while it provides a higher probability of being in very good, good and fair health. For the probability of a given child being in poor health, we find that both models provide very similar estimates. The cumulative difference in the probabilities (in absolute value) over all health categories between the parametric and nonparametric models is 11.1%, which is quite large.

As mentioned, one of the main objectives of this work is to understand whether nonparametric techniques can provide further insight into the income-health gradient in childhood. Thus, we focus more closely on how the income-health relationship changes with age, in particular for high- and low-income children.

Firstly, we examine how the probability of being in each health category changes with age (Figure 2.3). For children reported to be in excellent health, we find that the probability of being in that state varies little with age. On the opposite end of the health spectrum, we find that the probability of being in poor health also exhibits little change with age. We find the same pattern for the probability of being in very good, good and fair health.

On the one hand, this finding may suggest persistency of being in a given health status, as found in adult populations (Contoyannis et al., 2004). On the other hand, it may be a result of the type of question asked of the PMK when assessing a child's health status over time[7]. This result merits further investigation.

[7]When reporting a child's health status, the PMK uses other children of the same age as a

Next, we examine the conditional probability of being in excellent health, specifically for high- and low- income children (Figure 2.4). We define low-income children as those whose household income is at or below the 10^{th} percentile of the income distribution, whereas high-income children are defined as those whose household income is at or above the 90^{th} percentile. The probability of being in excellent health for each group of children is quite smooth with age. For all ages, high-income children have a higher probability of being in excellent health than low-income children; this is in line with the existing literature. The probability of being in excellent health is roughly constant with age for both high-and low-income children. The gap (difference) in the conditional probabilities of being in excellent health for these two groups of children is also roughly constant with children's age.

We also look at the health difference between high- and low-income children in the poor health category in the same vein as Currie and Stabile (2003)[8]. Currie and Stabile (2003) found that the incidence of children in poor health is higher at every age for those below the low-income cut-off. Moreover, their results suggest that the health gap between high- and low-income children widens with age, particularly for later ages. When we look at the probability of being in poor health for high- and low-income children, we find little change in the values (Figure 2.5). A closer look at these conditional probabilities reveals a very similar picture to the one found by Currie and Stabile (2003). Nonetheless, we do not focus too much on this result as we are dealing with very small probabilities.

reference point. Therefore, while there may be changes in the health distribution over time, if the child remains in the same relative health, we will not be able to pick up this effect.

[8]See Figure 2 from Currie and Stabile (2003).

Moreover, we look at different income cut-offs to define high- and low-income to assess the robustness of our results. An alternative is to consider low-income children as those who household income is at or below the 25^{th} percentile and high-income children as those whose household income is at or above the 75^{th} percentile. When high- and low-income is defined as such, we find that the difference in the probability of being in excellent health between these two groups of children decreases to the point that both curves are almost coincident. This suggests that as we look move away from the tails of the income distribution health inequalities become less significant, at least for children reported to be in excellent health.

In Chapter 1, we found that the inclusion of parental health in the Currie and Stabile (2003) model provided very different results from the authors' original findings. The inclusion of parental health proved to have an important role in explaining the income-health gradient in childhood and, more specifically, its behaviour with age. In order to assess the importance of parental health in the current framework, we analyse how our results change when parents' health status is excluded from our model. This is achieved by smoothing out parents' health, i.e., by assigning their corresponding bandwidths with the value of their upper limit.

We find a downwards parallel shift of the probability of being in excellent health for both high- and low-income children, but the gap between the two does not change (see Figure 2.6). On the other hand, for the probability of being in poor health, we find no change (Figure 2.7). What is interesting is that when parental health status is excluded from the model, our conclusions do not change. Contrary to our findings in Chapter 1, the exclusion of parental health from the model has little or not impact on our results – the income gradient in child health remains constant, with or without the inclusion of parents' health status.

We also excluded from our model the health status of each parent individually to assess the impact on our results. When father's health status is excluded, we find no change in our model predictions for the probability of being in excellent health. Thus, our results suggest that father's health does not have an impact on the probability of a child being in excellent health, regardless of household income. However, when we exclude mother's health status alone, we find predictions similar to those obtained when both parents' health are excluded.

In sum, the exclusion of parental health has an impact on the estimated probability of children being in excellent health, regardless of household income but, consistent with the literature, the greater impact on child health is associated with the health of the mother. Moreover, the exclusion of parental health from our model does not change our conclusions regarding how the income-health gradient behaves in childhood, contrary to previous work (see Chapter 1).

2.6 Discussion

When analysing self-reported health status, economists tend to employ either the ordered probit or logit specifications since they are particularly useful models to analyse variables that take on ordered outcomes. However, in practice, we seldom know the functional form of the object we are estimating or the underlying distribution of the error term. Nonparametric techniques have an advantage since these do not impose any distributional assumptions.

We find different results when we compare the predictions from our parametric and nonparametric models. For the nonparametric model we have a higher in-sample CCR than the parametric model. Some researchers may argue that this is an artifact of overfitting. However, we also obtain a higher out-of-sample CCR with our nonparametric model. Thus, when we estimate our model on independent data we continue to obtain a much better model fit. Both of our models are an approximation of the true data generating process. However, the more appropriate model is expected to perform better on independent data drawn from the same process. This result provides evidence that our nonparametric model is closer to the true data generating process.

When we estimate our nonparametric model on the full sample, we find that it provides an improvement of about 35% compared to its parametric counterpart. Moreover, we find quite similar CCRs whether we estimate our model in or out-of-sample, which provides robustness to our results. Thus, the nonparametric model provides a more realistic depiction of the income-health relationship for children.

Our proposed model includes a variety of covariates which we expect to have significant impacts on children's health status. However, given our estimated smoothing parameters, we find that controls for cohort (year dummies), whether a child lives in a two-parent household, birth order and the physical state of the house the child lives in are not relevant predictors of child health. All other explanatory variables, such as the log of household income, log of family size, child's age, mother's age, dummy variables indicating a child's sex and ethnicity (white vs. non-white), whether the PMK is female, whether the mother and father are in poor health and smoke, and the mother and father's educational attainment, were found to be significant within our model framework. Previous research found that the physical state of the home is a strong predictor of child health (se Chapter 1); we provide evidence that refutes this finding.

When we compare high- and low-income children, we find that the probability of being in excellent health does not change with age. Moreover, the health gap between high- and low-income children in excellent health is roughly constant with age.

Our results suggest that a child's initial health endowment and the income of the household in which they live are strong predictors of the probability of being in a given health category at older ages. Thus, we find persistency of being in a given health category with age.

Our results also confirm the importance of parental health, especially maternal health, and health behaviours in explaining child health. Parents' health status has an important impact on the probability of being in excellent health, regardless of household income. This implies that information on whether a parent is in good or poor health is required in order to have a full understanding of a child's own health status. To neglect the inclusion of these two variables in the model can lead to an incomplete understanding of the determinants of child health. However, we find that the exclusion of the parental health status variables in our model framework does not change our findings concerning the behaviour of the income gradient in child health, contrary to our findings in Chapter 1. Thus, this finding suggests that the key to a true understanding of the income-health gradient in childhood lies in specifying the relationship correctly (or at least more 'flexibly').

Hall et al. (2004) propose an estimator that deals effectively with various data types (continuous, nominal and ordinal); we make use of this estimator in our analyses. Most kernel methods presume that all variables included in the model are relevant. However, when this is not the case existing results such as convergence rates and the behaviour of bandwidths no longer hold (see Hall et al., 2004; Li and Racine, 2004b). One of the key features of this estimator is its ability to automatically remove irrelevant covariates from the model. It is possible that the least squares cross-validation method may have incorrectly removed relevant variables by selecting a too-large value of bandwidth. However, Hall et al. (2004) prove that the probability of this occurring converges to 0 as $n \to \infty$ (see Theorem 2 from Hall et al., 2004). Given the size of our sample it is unlikely that this finding is an error.

2.7 Conclusion

Case et al.'s (2002) study found a positive relationship between child health and household income, and provided the impetus for others to investigate this relationship further using data from other countries. This work has typically employed an ordered probit framework to examine child health status. To our knowledge, no other research has analysed this topic using nonparametric techniques.

Our nonparametric model provides a better alternative to estimating each of the individual health categories, as parametric models sometimes tend to provide corner solutions, which can bias our understanding of child health. Our nonparametric model provides an improvement of 33% and 31% for in- and out-of-sample predictions, respectively, when compared to our parametric model. Therefore, even when we estimate our model on independent data we continue to obtain a better model fit, evidence that our nonparametric model is closer to the true data generating process.

The results further our understanding of how household income impacts child health. By examining the end categories of the ordered health status variable, we provide insight on how the probability of a child being in excellent or poor health changes with both the child's age and household income.

Our results support the conclusion that there is an income gradient in child health; that is, children in higher income households are more likely to be in better health. Moreover, the difference in the probabilities that children in high- and low-income families will be in excellent health is roughly constant with age.

Our results also suggest that children's initial health endowment is a strong predictor of their subsequent health status. Furthermore, we confirm the importance of parents' health, especially that of the mother, in explaining child health.

However, contrary to earlier work, including that reported in Chapter 1, we find that the income-health gradient is not affected regardless of whether parental education is included in the estimation. Importantly though, the magnitude of the estimated health-income relationship is similar, whichever estimation process is used.

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APPENDIX

We hold values for all explanatory variables constant at their median/modal values, which are as follows: year dummy (1996), age (4), log of household income (10.85, which corresponds to $51 534), log of family size (1.39, which corresponds to 4 family members), dummy variable indicating whether the child is male (1), dummy variable indicating whether the PMK is female (1), dummy variable indicating whether the child lives in a two parent household (1), mother's age (28), dummy variables indicating whether the mother and father are in poor health (0), the child's birth order (2), dummy variable indicating the child' ethnicity (white vs. non-white) (1), dummy variables indicating whether the mother and father smoke (0), variables indicating the mother and father's level of educational attainment (3) and dummy variable indicating whether the house is in need of repairs (0).

Table 2.1: Summary Statistics

Covariates	**Mean**	**Covariates**	**Mean**
Child Health	1.551	Two-parent household (%)	0.996
	(0.747)		(0.061)
Household income	57,620	Mother - poor health (%)	0.214
	(35,383)		(0.431)
Child's age	6.754	Father - poor health (%)	0.223
	(3.893)		(0.431)
Male (%)	0.506	Mother - smoking (%)	0.246
	(0.500)		(0.431)
White (ethnicity) (%)	0.813	Father - smoking (%)	0.256
	(0.390)		(0.437)
Birth order	1.754	Mother's education	2.562
	(0.880)		(0.959)
Family size	4.366	Father's education	2.421
	(0.981)		(1.051)
Female PMK	0.934	Household in need of repairs (%)	0.240
	(0.248)		(0.427)
Mother's age at child's birth	27.945	**Number of observations**	**33,426**
	(4.701)		

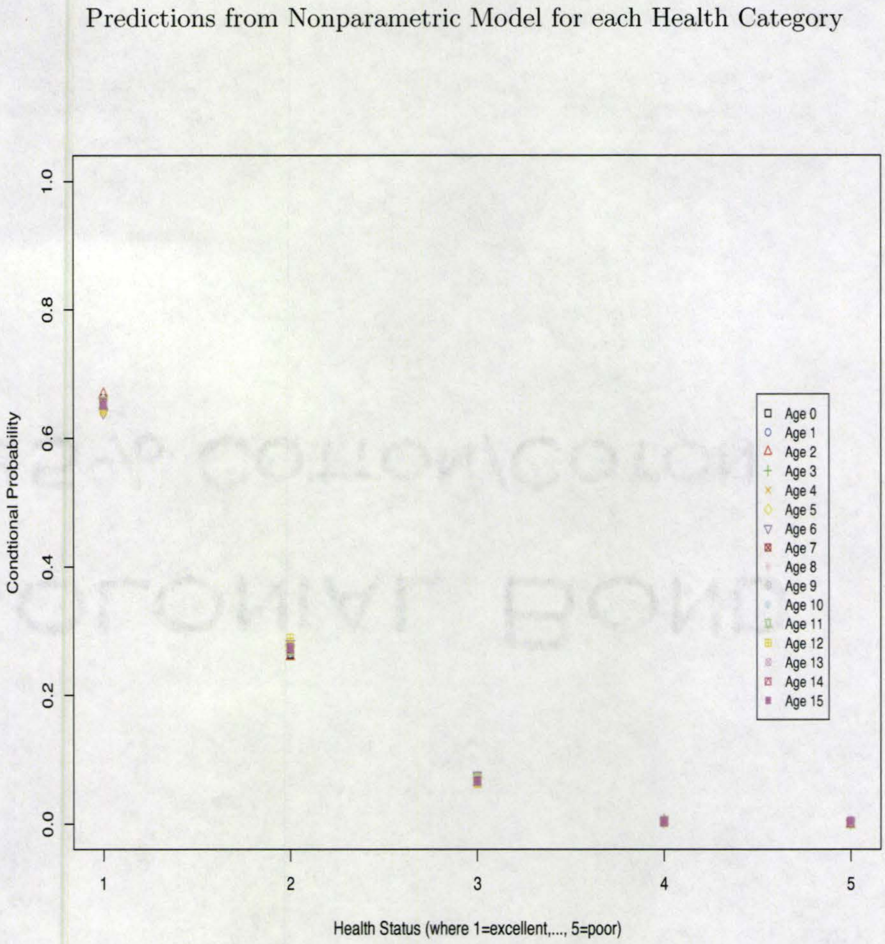
Note: Standard deviations are in parentheses.

Table 2.2: Cross-validation Selected Smoothing Parameters

Covariates	$\widehat{h}$, $\widehat{\lambda}$	**Upper Bound**
Household income	0.419	∞
Child's age	0.925	1
Male	0.377	0.5
White (ethnicity)	0.131	0.5
Birth order	1	1
Year of cycle	1	1
Family size	0.154	∞
Female PMK	0.312	0.5
Two-parent household	0.5	0.5
Mother's age at child's birth	0.806	1
Mother - poor health	0.066	0.5
Father - poor health	0.135	0.5
Mother - smoking	0.22	0.5
Father - smoking	0.196	0.5
Mother's education	0.425	1
Father's education	0.488	1
House in need of repairs	0.5	0.5

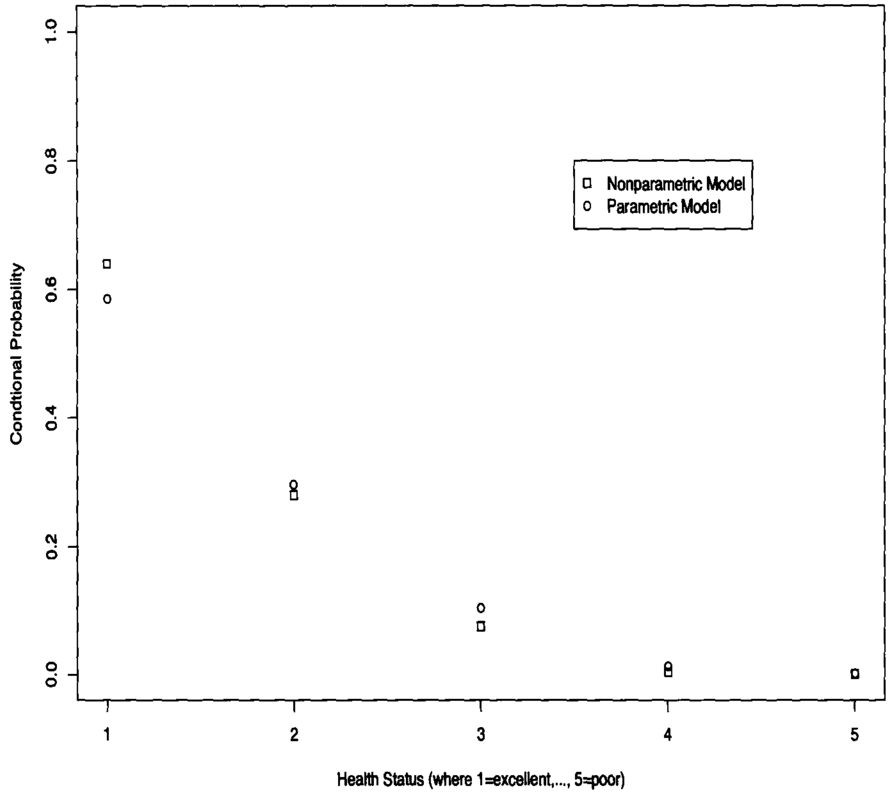
Note: $\widehat{h}$, $\widehat{\lambda}$ are the estimated cross-validation smoothing parameters for continuous and discrete variables, respectively. For continuous variables the upper value for h is ∞, whereas for ordered discrete variables the upper value for λ is 1 and, for unordered discrete variables the upper value for λ is 0.5.

Figure 2.1: Conditional Probability of being in each Health Category for each Age



Note: We find that there is more variability across each health category than within a given health category for the different ages. For example, the conditional probability of being in excellent health varies from 0.62 to 0.68, while the probability of being in very good health varies from 0.22 to 0.28 (considering all ages).

Figure 2.2: Comparison between Parametric and Nonparametric Models
Comparison of Predictions from Equivalent Parametric and Nonparametric Models for each Health Category



Note: The parametric model yields a lower estimate of the conditional probability of being in excellent health, while it provides higher estimates for the conditional probabilities of being in very good, good and fair. Both models provide similar predictions for the probability of being in poor health. The cumulative difference in the probabilities (in absolute value) over all health categories between the parametric and nonparametric models is 11.1%, which is quite large.

Figure 2.3: Conditional Probability of being in each Individual Health Category

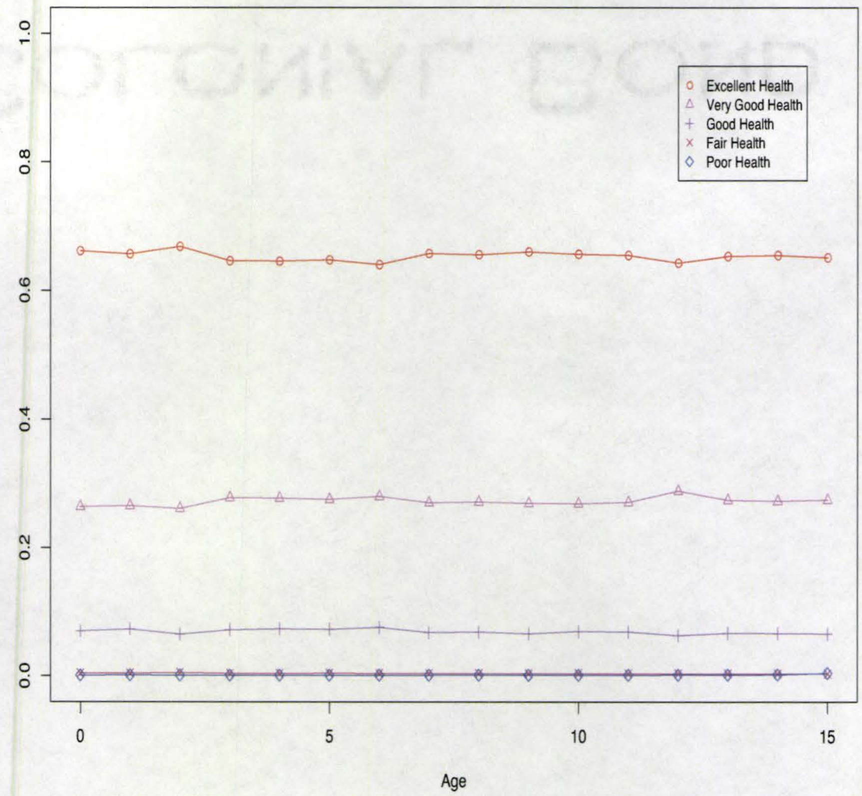


Figure 2.4: Conditional Probability of being in Excellent Health for High- and Low-Income Children by Age

Depiction of the Income-Health Gradient for Children in Excellent Health

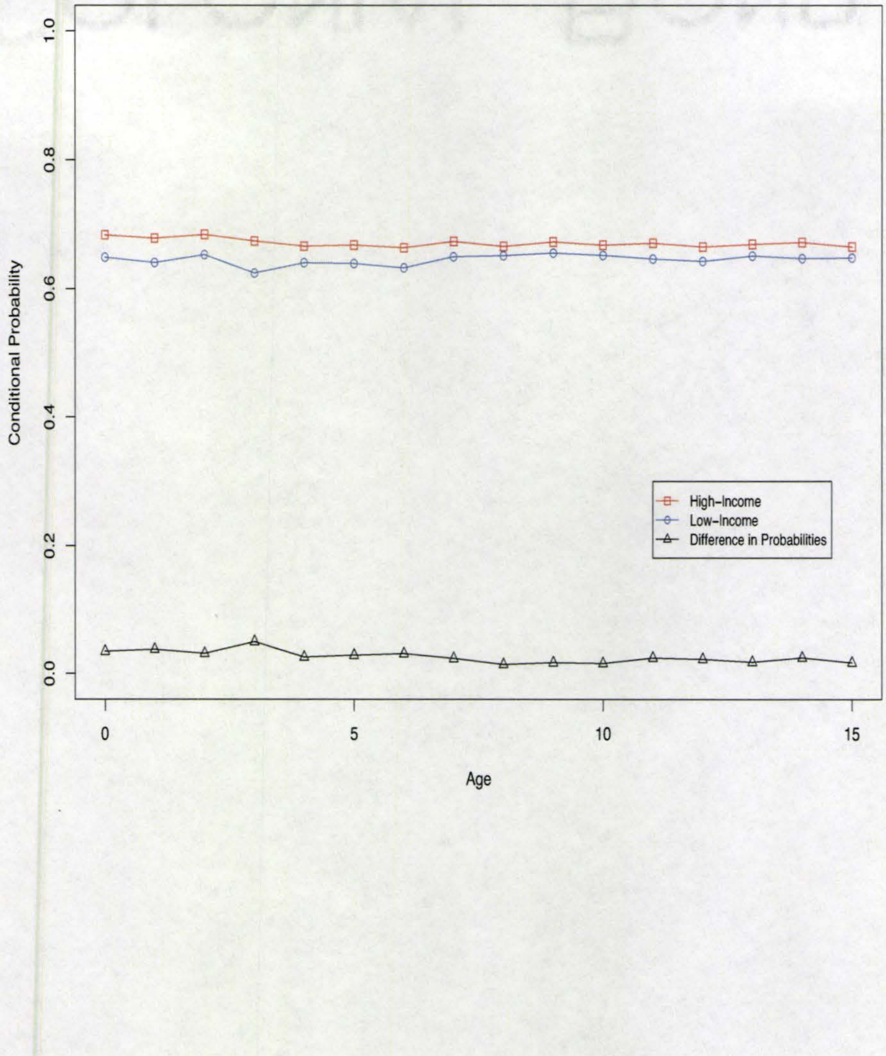
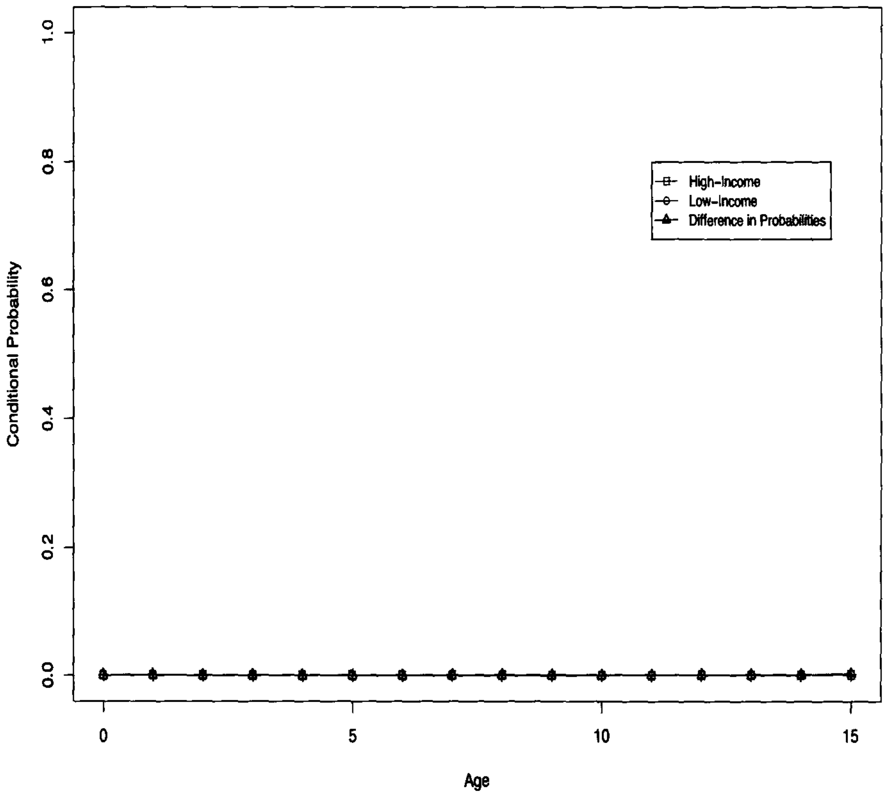


Figure 2.5: Conditional Probability of being in Poor Health for High- and Low-Income Children by Age

Depiction of the Income-Health Gradient for Children in Excellent Health



Note: All lines are coincident.

Figure 2.6: Conditional Probability of being in Excellent Health for High- and Low-Income Children by Age when Parents' Health is Smoothed Out

Depiction of the Income-Health Gradient for Children in Excellent Health when Parents' Health Status is Removed from the Model

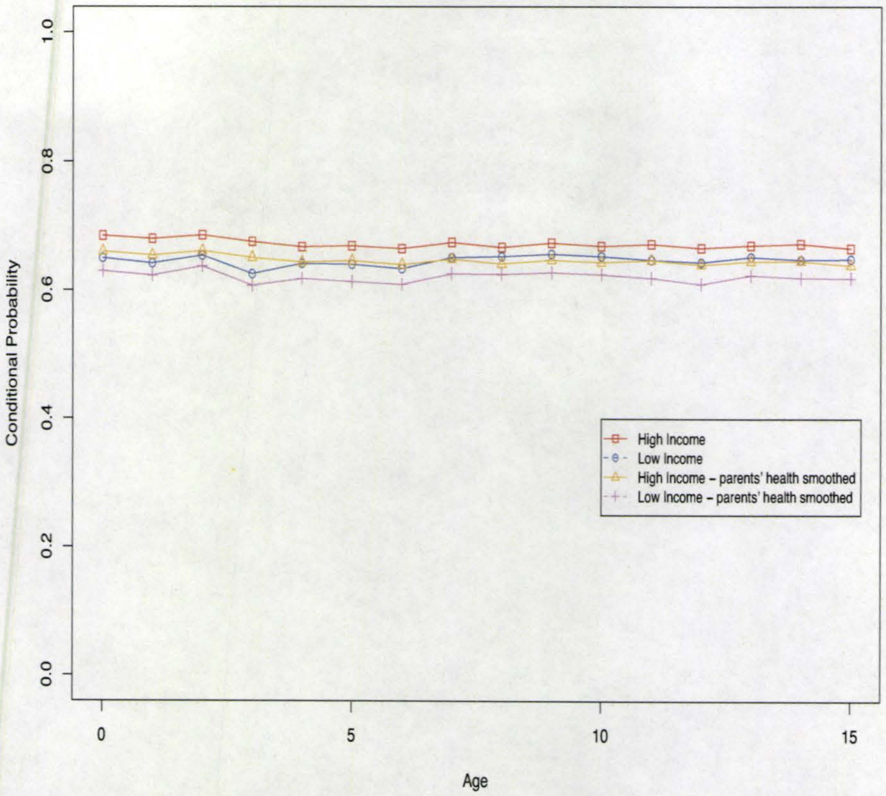
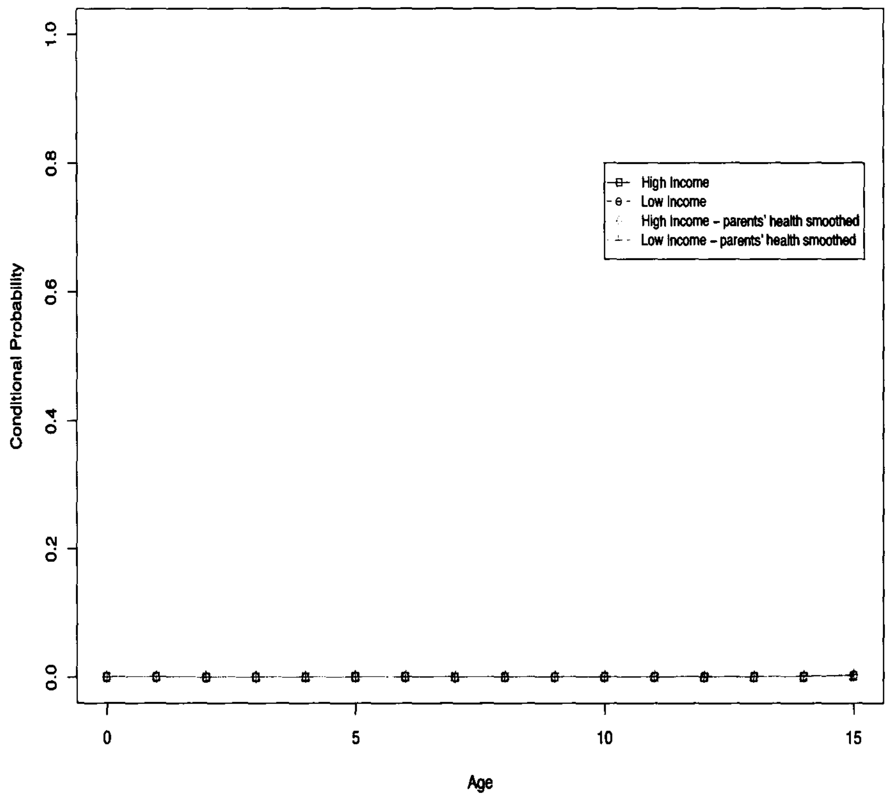


Figure 2.7: Conditional Probability of being in Poor Health for High- and Low-Income Children by Age when Parents' Health is Smoothed Out

Depiction of the Income-Health Gradient for Children in Poor Health when Parents Health Status is Removed from the Model



Note: All lines are coincident.

Chapter 3

The Role of Chronic Conditions in Canadian Children's Health Status

3.1 Introduction

In Chapter 1, we set out to understand whether, using a new framework, there was an income gradient in children's health. Furthermore, we were interested in understanding how the income-health gradient behaved with child age. We found that the inclusion of parental health in the Currie and Stabile (2003) model reduces the magnitude of the effect of income on child health and, more importantly, leads to a case where the income-health gradient does *not* increase with age.

In this chapter, we are concerned with understanding further *why* the income-health gradient exists in childhood and the underlying factors that may help explain this relationship. It has been documented that low-income children have poorer health compared to their high-income counterparts. However, the reasons for this finding are poorly understood. Some authors have found that low-income children are subject to more health shocks in the form of chronic conditions or other health insults (Case et al., 2002; Currie and Lin, 2007; Currie and Stabile, 2003; A. Currie et al., 2006). Previous research has also shown that chronic conditions in childhood have a long-reaching impact on adult outcomes (Case et al., 2005). We propose to examine how chronic conditions impact child health and whether this effect differs by income level.

Case et al. (2002) find that the relationship between child health and household income for the US is positive and becomes more pronounced as children age. They find that part of this relationship can be explained by the impact of chronic conditions – children from lower-income households with chronic conditions have worse health status than do those from higher-income households. A. Currie et al. (2006) follow Case et al. (2002) by investigating the role of chronic conditions in determining the income-health gradient for British children. The authors find little evidence that income protects child health from the adverse effects of chronic conditions.

Currie and Stabile (2003) also examine whether the accumulation of chronic health conditions plays a role in the gradient. However, unlike to the previous two studies, the authors make use of longitudinal data on Canadian children. Their results suggest that the existence of the income-health gradient can be attributed to the fact that low-income children are more likely to suffer from health shocks in the form of chronic health conditions.

Our main objective is to extend Currie and Stabile's (2003) analysis by examining the impact of chronic conditions and activity limitations on child health. To do so, we examine this issue on three fronts. First, we analyse the role of household income on the prevalence of chronic conditions and activity limitations among children. Second, we assess the impact of chronic health conditions and activity limitations on children's general health status. Third, we assess how high- and low-income children differ with regards to the impact of chronic health conditions and activity limitations on general health.

Our results show that income does not have a significant impact on the prevalence of child chronic health conditions. Moreover, we do not find the effect of chronic health conditions on the probability of being in poor health differs by income levels, with the exception of asthma and mental handicap. Thus, our findings do not support the hypothesis that income protects children from the adverse impact of chronic conditions. In addition, we do not find any evidence that the income effect becomes stronger with age. These findings suggest that income-related policies may have little or no impact in improving child health.

In the next section, we provide an overview of the existing work on this topic. Following the literature review, we describe the data used in our analyses. We then look at the models, followed by the results and discussion sections. We conclude with a summary of our findings.

3.2 Literature

In Chapter 1, we found that the income gradient in children's health is constant and, therefore, the difference in health status between high- and low-income children does not change throughout childhood and early adolescence. Case et al. (2002) suggest that an important priority for future research is to identify the mechanisms that underlie the relationship between household income and child health. We propose to address this call within the Canadian context.

Many researchers have documented that poor children suffer more insults to their health than richer ones do. Paul Newacheck, Neal Halfon, and Anne Case and colleagues, among others, show that poor children are more likely than others to suffer from chronic conditions.

In their seminal paper, Case et al. (2002) examine whether the accumulation of chronic conditions plays a role in explaining the gradient using data from the National Health Interview Survey (NHIS), from 1986 to 1995. The NHIS is a cross-sectional survey that collects annual data on health status and chronic and acute medical conditions of American adults and children. The authors examine the probability of a given child having a potentially serious chronic condition[1]; a listing of these conditions can be found in Table 1.

The American evidence indicates that poor children are more likely than wealthy children to experience some (although not all) chronic conditions. This supports the idea that income (or characteristics associated with income) protects children from

[1]The authors did not consider conditions that rarely occur in childhood.

the adverse effects of chronic conditions. Case et al. (2002) find that the gradient is largest for the more severe chronic conditions such as asthma, diabetes, epilepsy, kidney disease and mental retardation. The differences in the prevalence of chronic conditions across income groups explain part of the association between income and health status. In addition, among US children with the same health conditions, those from wealthier families are reported to be in better health than those from poorer ones, suggesting that the chronic conditions of wealthier children are less severe, or better managed.

A. Currie et al. (2006) follow Case et al. (2002) by investigating the role of chronic conditions in determining the income-health gradient for British children. They also examine the probability of a given child having a chronic condition using the Health Survey of England (HSE) from 1997 to 2002. This survey collects information on whether a child has a long-term chronic health condition, the type of condition and whether the condition limits his/her normal day-to-day activities. Up to a maximum of six different chronic health conditions are recorded for each child and subsequently these are grouped into 42 categories in the HSE data files, which the authors have further grouped into 12 broad categories (see Table 3.1 for more details on this).

A negative income gradient is evident for only 3 of the 12 chronic conditions examined – asthma, mental illness/mental handicap/epilepsy/other problems of nervous system and skin complaints. These results are in line with Case et al. (2002) who found that the income gradient was largest for asthma and mental retardation.

A. Currie et al. (2006) also investigate whether children from richer families are less affected by chronic illnesses than poorer children. Their results differ from

Case et al. (2002) in that a number of the chronic conditions they examine are not associated with worse health status. The authors find that most chronic health conditions have a positive effect on the probability of being in poor health. In particular, they find that 3 conditions are significant in determining general health status, namely mental illness/mental handicap/epilepsy/other problems of nervous system; diabetes (including hyperglycaemia)/other endocrine/metabolic conditions; and hypertension/high blood pressure/blood pressure related problems. Furthermore, A. Currie et al. (2006) find little evidence that income protects health status from the adverse effects of chronic conditions.

As a follow-up to A. Currie et al.'s (2006) work, Anne Case, Diana Lee and Christina Paxson (2008) published a recent article in the Journal of Health Economics. This paper re-examines the differences found between the income gradients in American and English children's health; the authors also examine the impact of chronic conditions on child health. Case et al. (2008) find that the A. Currie et al.'s (2006) measures of chronic conditions were incorrectly coded[2]; they present and discuss results based on correctly coded data from the HSE in their paper. Case et al. (2008) examine the impact of four chronic conditions – asthma, bronchitis, blindness or vision problems and digestive problems – that are roughly comparable across both surveys (the NHIS and the HSE) and that have a prevalence rate greater than 1% in the HSE. The authors find that the effects of chronic conditions on health status are larger in the English sample than in the American one, and that income plays a larger role in buffering children's health from the effects of chronic conditions in

[2]This was confirmed through personal correspondence with one the authors.

England.

Nahum (2006) also takes on a similar approach to Case et al. (2002), while looking at 9 different chronic conditions as described in Table 1. Nahum (2006) makes use of the Swedish Survey of Living Conditions and finds no significant income effect on the prevalence of any chronic health problem among children. However, she finds some evidence that households with liquidity problems face a greater probability of having a child with chronic health problems.

Finally, using Canadian data, namely the Quebec Longitudinal Study of Child Development, Lefebvre (2006) examines the role of chronic conditions in determining child health using the same approach as Case et al. (2002)[3]. Lefebvre looks specifically at impact of asthma and other chronic conditions on the health of children ages 5 to 41 months (see Table 1). The author finds that, on average, income does not have a significant impact on the probability of a given child having a chronic condition. Moreover, Lefebvre finds that income decreases the probability of a child being in poor health, while the presence of asthma/chronic health problem in childhood has a strong positive impact on the probability of being in poor health. Finally, the author finds no differential income effect for asthma/chronic conditions, contrary to Case et al.'s (2002) results.

Also drawing on Case et al.'s (2002) seminal work, but taking a slightly different approach, Currie and Lin (2007) explore the extent to which health insults and activity limitations are responsible for the fact that low-income children are in worse

[3]Currie and Stabile (2003) also examine the impact of chronic conditions on child health using Canadian data. However, with the exception of asthma, the impact of chronic conditions on child health was not examined individually, but rather jointly in the form of a health shock.

health than high-income children. The main objective of their paper is to have a better understanding of why poverty/low income is linked to ill health by looking at the relationship between poverty, overall health status, health insults, and activity limitations resulting from health problems, using the 2001-2005 NHIS. More specifically, the authors are concerned with understanding which health measures are associated with better assessments of overall health and whether specific health conditions have larger effects on the overall health status of poor children.

Compared to Case et al. (2002), Currie and Lin (2007) examine a more recent time period, while broadening the scope of previous work by including mental health conditions, acute illnesses and injuries. Furthermore, they investigate whether controlling for specific health conditions and limitations measured in the NHIS reduces the effect of poverty on child health.

They find that in 2001-2005 poor children were more likely than rich children to be affected by each type of negative health shock. They find that asthma, mental health problems, and trouble seeing or hearing are among the most limiting chronic conditions in childhood. Poor children with these conditions are more likely to be limited in their activities. Moreover, the impact of these chronic conditions on child health tends to grow faster over time.

The impact of child chronic health conditions is visible not only during childhood and adolescence but also later on in life during adulthood, on outcomes such as health, education, employment and earnings. Case et al. (2005) provide evidence on how chronic conditions in childhood have lasting effects over the life course for British children. Among other health measures, they look at physician-assessed chronic conditions at ages 7 and 16, namely physical impairments; mental and emotional conditions; and other systems conditions. Their findings highlight the potential role of health status as an intergenerational transmission mechanism of economic status. Children born into poorer households are more likely to experience poorer health during childhood and face a higher incidence of chronic conditions, but also more likely to make lower investments in educational attainment, which have long lasting impacts on adult health and socioeconomic status.

Dooley and Contoyannis (2008) also explore the impact of child chronic health conditions and activity limitations on adult outcomes, such as adult health, educational attainment, earnings and wages, and hours worked. The authors use the Ontario Child Health Study which follows children into their late twenties and early thirties. Their results indicate a substantial impact of childhood chronic conditions/ activity limitations on both schooling and health outcomes in young adulthood and, consequently, on labour market outcomes for both men and women.

3.3 Data

In our analysis, we make use of Statistics Canada National Longitudinal Survey of Children and Youth, cycles 1 to 3. The National Longitudinal Survey of Children and Youth (NLSCY) is a long-term study that follows Canadian children's development and well-being from birth to early adulthood. The NLSCY began in 1994 and is jointly conducted by Statistics Canada and Human Resources and Social Development Canada (HRSDC). The study is designed to collect information about factors influencing a child's social, emotional and behavioural development and to examine the impact of these factors on the child's development over time.

The target population was aged 0 to 11 at the time of their selection in Cycle 1, in 1994, and living in Canada's 10 provinces. The survey excludes children living on Indian reserves or Crown lands, residents of institutions, children of full-time members of the Canadian Armed Forces, and residents of some remote regions.

The NLSCY is a longitudinal survey consisting of several longitudinal and cross-sectional samples. All children are drawn from the Labour Force Survey's (LFS) sample of respondent households. The observations used in our analyses include children from the longitudinal cohort between the ages of 0 and 15. We start off with 14,162 children present in all three cycles. Due to the availability of information on the variables included in our model, our final sample is reduced to roughly 11,000 children per cycle. We use the same sample employed in Chapters 1 and 2 for the de Oliveira model (n = 33,426). For the analysis of this chapter we lose roughly 400 observations on children for whom we do not have information on either chronic conditions or activity limitations in any of the three cycles. All information used in our analyses is reported by the person most knowledgeable (PMK) about the child.

3.3.1 Measuring Child Health

The NLSCY collects information on a series of chronic conditions that children may experience, such as asthma/wheezing/whistling in the chest; respiratory allergies;

bronchitis; heart condition or disease; epilepsy; cerebral palsy; kidney condition or disease; mental handicap; learning disability (available for children 6-15 only); emotional, psychological or nervous difficulties (available for children 6-15 only); and any other long-term condition[4]. Precise estimates of the effects of rare chronic conditions on health status require large sample sizes. The NLSCY sample is too small to examine how rare childhood conditions such as epilepsy and cerebral palsy are related to health status. Because of this, we have grouped some chronic conditions together into broader categories in an effort to increase the sample size. In addition to general health status and child chronic conditions, we include activity limitations in our analysis.

The NLSCY does not inquire about whether children have diabetes compared to other surveys that collect information on child health. This is worth highlighting, given that this chronic condition tends to be somewhat frequent among children.

The NLSCY also does not have any information on functional limitations available in other surveys, such as mobility or blindness. We do have information regarding the Health Utilities Index; however, this information is not available for all ages (this information is only available for children ages 4-12) ; thus, we have not included these variables in our analysis.

There has been some concern with regards to the reporting of child health. In the NLSCY, child general health is reported by the PMK, the person most knowledgeable about the child. This measure is commonly used in the literature. Although the PMK reports whether the child has a chronic condition, he/she is asked to report on an

[4]This is the exact notation used in the NLSCY.

assessment made by a health care professional. Thus, we feel that the reporting of chronic health conditions is based on a more objective assessment[5].

3.3.2 Measuring Child and Parental Characteristics

We now provide a description of the explanatory variables included in our model, henceforth known as the *de Oliveira* model. The main socioeconomic status variables are household income (natural log), mother's education, and father's education. Each parents' educational attainment was classified into one of four categories (1- less than secondary school; 2 - secondary school graduation; 3 - beyond high school; and 4 - college or university degree (including trade), where the first is the omitted case). Household income is reported by the PMK in dollars, and adjusted for price inflation using the Canadian Consumer Price Index. (When income is not reported, Statistics Canada imputes a value.) In our analyses, we make use of each household's current income. However, as a robustness check, we also estimate our models using each household's permanent income to see if this variables changes our results.

We control for a series of child and parental characteristics: family size (natural log), the mother's age at the child's birth and dummies to indicate child age; child sex; child ethnicity (white vs. non-white); whether the PMK is female; whether the mother and father are in poor health and whether the mother and father smoke[6]. Finally, we include the PMK's depression score as this variable has been found to

[5]Some may argue that physician assessments may reflect diagnosis biases. While this may certainly happen, there is no easy way to circumvent this problem in our data.

[6]The choice of our control variables has been influenced, in part, by the results of our nonparametric model in de Oliveira (2008).

have a significant impact on children's physical health. This variable takes on a value from 0 to 40, where 0 represents an absence of depression.

Although we are working with longitudinal data, in practice we do not make use of the panel nature of the data. We do this mainly for two reasons: first, we wish to replicate the analysis of chronic conditions by Case et al. (2002); second, because we are dealing with rare childhood conditions, by pooling the data we are able to increase our sample size[7].

Summary statistics can be found in Table 3.2 (where all three cycles of data have been pooled). The most common common chronic health conditions are asthma and allergies; this tends to be the case in most of the developed world. The least prevalent chronic health conditions are epilepsy and cerebral palsy. About 29% of children in our sample have been diagnosed with a chronic condition or activity limitation at some point during the three cycles in which they are observed. The average household income is roughly $49,500 Canadian dollars. Our sample is comprised of roughly the same number of boys and girls; the typical family is white and has four people. The parents of these children are relatively healthy and well educated compared to the Canadian population.

[7]For some child chronic conditions, we have such small numbers that the release of these data would lead to potential disclosure issues.

3.4 Methods

It has been found that low-income children have poorer health outcomes than children from high-income families. In what follows, we seek to further understand the possible factors/life circumstances that explain this finding. Although we do not make use of the panel nature of the data for our models, we adjust the standard errors to account for repeated observations for the same child[8].

We estimate models of this type in the same vein as Case et al.'s (2002) original work. However, in order to correctly identify the effect of income on child health, one needs to estimate fixed effect models; we leave this task for future work.

First, we replicate Case et al.'s (2002) models using our data; then, we estimate the same models using the de Oliveira framework. Following Case et al. (2002), we estimate linear probability models for the probability of a child having a given chronic condition (C), where household income, ln(inc), is one of the independent variables. Other independent variables (X) include those mentioned previously[9].All observations are clustered by child ID.

$$C = \alpha_0 + \alpha_1 \; ln(inc) + X\delta^C + \epsilon^C \tag{3.1}$$

We are interested in understanding whether poorer children are more likely to suffer from chronic conditions (in which case α_1 is negative). We also estimate the

[8]All observations were clustered by child ID to account for this. Moreover, we specify a Huber/White estimator (Huber, 1967; White, 1980), which provides corrected robust standard errors.

[9]The X matrix for the Case et al. (2002) model includes a complete set of age dummies, year dummies, the logarithm of family size, and indicator variables for whether the child was male, white, or black.

probability of a given child having an activity limitation, any given chronic condition and, finally, the probability of having either a chronic condition or an activity limitation.

In addition, we analyse the impact of chronic conditions and household income on child general health status. In this model (see equation 3.2), the dependent variable is a binary outcome indicating whether a child is in good or poor health, where good health is defined as being in excellent and very good health, and poor health is defined as being in poor, fair or good health. Once again, we replicate Case et al.'s (2002) model and then estimate the de Oliveira model. In both cases, and in line with Case et al. (2002), we express income as deviations from mean income to interpret more readily the coefficients as the effect of income at the mean.

We follow Case et al. (2002) by investigating which chronic conditions have the most serious impact on child health. We also examine the possibility that children from richer families are less affected by, or more 'protected' from, chronic illnesses than those from poorer families. To evaluate this assumption, we include interactions of income with each chronic condition. All observations are clustered by child ID.

$$H = \beta_0 + \beta_1 \; [ln(inc) - \overline{ln(inc)}] + \beta_2 \; C + \beta_3 \; [ln(inc) - \overline{ln(inc)}] \; C + X\delta^C + \epsilon^C \quad (3.2)$$

It is plausible that the adverse effects of chronic conditions, and the protective role of income in their presence, become more pronounced with the length of time the child has the condition. We do not observe the date of onset of each of these conditions. However, for conditions that are realised at young ages, older children will, on average, have had conditions for longer periods. By estimating equation (2) separately for younger (0-8) and older (9-15) age groups we can examine whether, in the cross-section, this coefficient is larger for older children.

Stata 9 was used for all estimation.

3.5 Results

The main objective of this paper is to extend Currie and Stabile's (2003) analysis by examining the role of chronic conditions and activity limitations on child health, while following the approach taken by Case et al. (2002). First, we estimate the Case et al. (2002) model in an effort to replicate Table 3 from their original paper. Second, we estimate the de Oliveira model. The sample of children employed in this model differs from that used in the Case et al. (2002) replication; this, because we lose observations on children that do not have complete information on the variables included in this model. Third, we estimate the Case et al. (2002) model using the sample of the de Oliveira model to check the robustness of our results.

For all cases, we assess the role of household income on the prevalence of chronic conditions and activity limitations among children. In addition, we examine the impact of chronic conditions and activity limitations on children's general health status and how the effect of these on child health differ by income.

3.5.1 Case et al. (2002) Model Replication

We begin our analysis by replicating Case et al.'s (2002) model. To do so, we employ the exact model specification as the authors did in their paper; the estimates can be found in Table 3.3. Unfortunately, due to data limitations, there are only a few chronic conditions that we can compare directly with Case et al. (2002) (see Table 3.1).

The most prevalent chronic conditions for Canadian children are asthma and allergies; in other words, respiratory conditions. This tends to be the case for children in developed countries. This was also found in Case et al. (2002) where the chronic conditions with the highest prevalence rates are for hay fever, bronchitis, asthma and sinusitis. The least common conditions for our sample are cerebral palsy; epilepsy; mental handicap and kidney condition or disease. The least prevalent in the Case et al. (2002) paper are diabetes, epilepsy and kidney disease.

For Canadian children, we find a higher prevalence of asthma than American children; this may be due to the fact that the variable we define as asthma includes not only asthma, but also wheezing and whistling in the chest. Case et al. (2002) do not have information on allergies as we do; however, they do have information on hay fever and sinusitis. Generally, allergies include hay fever (also know as allergic rhinitis) and sinusitis (allergies to the sinuses); the sum of the two prevalence rates for American children is closer to the Canadian rate. We can compare more closely bronchitis; heart condition or disease; epilepsy; kidney condition or disease; and mental handicap/mental retardation.

Model 1 examines the impact of income on the prevalence of a child having a given chronic condition. We find that the income coefficients are statistically significant and negative for asthma, bronchitis, heart condition or disease, epilepsy, learning disability and emotional and psychological or nervous difficulties. Among these conditions, we find that the steepest gradients are for asthma and bronchitis. For allergies, however, the income relationship is positive. That is, this chronic condition is positively related to income, consistent with Case et al. (2002).

For model 1, we estimate the impact of a doubling of income (from \$30,000 to \$60,000) on the probability of having asthma or bronchitis; we also estimate the income-health elasticities. When we double income, the probability of having asthma changes from 0.1378 to 0.1268, which translates into a decrease of 0.011, i.e., a 1.1 percentage point decrease. For the probability of having bronchitis, a doubling of income leads to a decrease in the probability of 0.0097, roughly 1 percentage point (from 0.0342 to 0.0245).

We also calculate the income-health elasticities for the probability of having asthma and bronchitis, respectively. For asthma, we find an income-health elasticity (in absolute value) of about 0.08 – when we increase household income by 1%, the probability of having asthma increases by 0.08%. For bronchitis, we find an income-health elasticity (in absolute value) of 0.28, much larger than the one found for asthma. Although small, these elasticities are consistent with those found in the literature (Blau, 1999).

Model 2 looks at how income and chronic health conditions impact child health and whether the impact of chronic conditions varies by income level. All income coefficients are negative, as expected; higher income decreases the prevalence of having a given chronic condition. Most coefficients are close in magnitude, ranging from about 0.039 to 0.046. All chronic condition coefficients are positive, as expected – the higher the prevalence of each chronic condition, the higher the probability of being in poor health. We find the largest coefficients are for epilepsy and mental handicap; this suggests that these conditions impact the probability of being poor health the most; these results are in line with those found by Case et al. (2002). Finally, we find that the coefficients associated with the income-chronic condition interaction term are negative, as expected. The only coefficients statistically significant are those for asthma and allergies (and mental handicap at the 10% level).

Case et al. (2002) test the hypothesis that the buffering effect of income is cumulative, i.e., income is more protective of children's health status at older ages. We find that very few of the β_3 coefficients are statistically significant; the only significant ones are those for asthma, and mental handicap but only for children 0-8[10]. This finding is contrary to Case et al.'s (2002) findings and does not support the hypothesis that the protective effect of income increases with age. Furthermore, and in line with Case et al.'s (2002) findings, the differences between coefficients for younger and older conditions are not statistically significant, with the exception of asthma (these two coefficients are significantly different at the 10% level).

[10]We also find the coefficients for allergies ages 0-8 and bronchitis ages 9-15 to be statistically significant at the 10% level.

3.5.2 de Oliveira Model

Second, we estimate the de Oliveira model; the results can be found in Table 3.4[11]. Once we control for a series of covariates, we find that for Model 1 income has an impact on the prevalence of bronchitis only. The magnitude of the estimated income coefficient is only half as great as the one with the Case et al. (2002) model. For this model, if we double income (from $30,000 to $60,000) we find that the probability of having bronchitis changes from 0.0305 to 0.0256, which translate into a decrease of 0.0049, roughly 0.5 percentage point; this is not a large change. When we estimate the income-health elasticity for the probability of having bronchitis, we find that a 1% increase in household income leads to a 0.16% decrease in the probability of a child having bronchitis.

The income coefficients for asthma, activity limitations and chronic conditions and/or activity limitations are not statistically significant; thus, we do not examine how a doubling of income impacts the probability of having these conditions or the resulting elasticities.

For Model 2, all income coefficients are negative as before. However, the income coefficient associated with asthma is no longer statistically significant. Once we control for a series of covariates, asthma no longer has an impact on the probability of being in poor health. As before, all coefficients associated with chronic conditions are positive and significant. In line with our previous model, the largest coefficients are found for epilepsy, cerebral palsy and mental handicap. For the β_3 coefficients,

[11] The results of the full regressions can be found in the Appendix.

we find that with the de Oliveira model some are positive, while other are negative, contrary to what we saw beforehand. The only significant coefficients are those associated with asthma and mental handicap. This result is in line with Case et al. (2002). Interestingly, the coefficient for asthma is negative but the one for mental handicap is positive. Moreover, this last coefficient is quite large in magnitude. This finding is quite bizarre and could be due to a reporting issue. On one hand, given the variable name, we may have misreporting due to a misunderstanding of what 'mental handicap' entails. On the other, it may be the case that there is some social stigma with having a child with a mental handicap, which could lead to the misreporting of its prevalence among low-income families.

Beyond chronic conditions, we also look at activity limitations as well as some combined measures (this in an effort to increase the sample size). Almost 30% of the children in our sample have either a chronic condition or an activity limitation or both. For Model 1, we find that income does not have a protective effect for any of the measures. As for Model 2, all coefficients are similar in sign and statistical significance with the other conditions. The income-chronic condition interaction term is significant for 'any chronic condition' and 'chronic health and/or activity limitation' variables only.

In comparing the younger and older age groups, we find that very few coefficients are significant and for the five conditions in which coefficients are significant, these are only significant for the younger age groups. The differences between coefficients for younger and older conditions are not statistically significant, with the exception of asthma (these two coefficients are significantly different at the 1% level).

In addtition, for Model 1 we find that the child's sex, the PMK's depression score and the mothers health status are significant predictors of the probability of a child having most of the chronic conditions examined in this Chapter. Curiously, for the probability of having either epilepsy or cerebral palsy we find that, besides age dummies, no other variable from our model is statistically significant. For the probability of having either a heart or a kidney condition, only the father's health and education matter. This finding is quite interesting as typically we find that maternal characteristiscs matter more than paternal ones.

For Model 2, once again, we find that the child's sex and parental characteristics play an important role in explaining the probability of a child being in poor health. More specifically, we find that for all regressions the PMK's depression score, the mother's health status, smoking habits and education as well as the father's health are statistically significant predictors.

We also estimate the Case et al. (2002) model using the same sample as the de Oliveira model to assess the robustness of our results (see Table 3.5). Compared to the Case et al. (2002) replication, we find that income is statistically significant for fewer conditions for Model 1. Furthermore, for Model 2 we find very few changes regarding the main results. In sum, when we change the sample the model's qualitative predictions generally hold.

In all of our regressions, we use current income to explain child health. However, one might think that long-term (i.e., average) family income might play a significant role in determining child health. An important issue within this context is whether the timing of income over a child's life has an impact on a childs health. In other words, it may make a difference as to what period of the child's life the child benefits from a higher family income.

For Model 1, we find that the income coefficients generally increase by a bit as well as the standard deviations; this is in line with the literature (Blau, 1999). Qualitatively, we find the same results as before. For Model 2, once again, we find that the income coefficients, and their respective standard deviations, generally increase in size. Qualitatively, we have the same conclusions[12]. Thus, although the impact of average income on child chronic conditions is marginally larger, our results are qualitatively the same whether we use current or permanent income.

3.6 Discussion

Most research has found that chronic health conditions play an important role in determining children's health. Our main objective with this work is to extend Currie and Stabile's (2003) analysis by examining the role of chronic conditions and activity limitations on child health. To do so, we analyse the role of household income on the prevalence of chronic conditions and activity limitations among children. Moreover, we assess the impact of chronic health conditions and activity limitations on children's general health status and how this impact varies with income.

Our results suggest that income has a greater protective effect for chronic conditions such as asthma, bronchitis, learning disabilities and emotional, psychological

[12]For the β_3 coefficients we find a rather large increase in size, that is, when we use permanent income in our regressions the impact of having a given chronic condition on the probability of having poor health is larger than when we use current income.

or nervous difficulties. Once we control for a series of socioeconomic variables, which we believe would help to explain child health, we find that income impacts only the prevalence of bronchitis and that the magnitude of this effect is reduced by half of its previous value. When we control for parental characteristics, such as health and education, for example, we find that the impact of income on the probability of having a given chronic health condition is no longer statistically significant. This is in line with Nahum's (2006) and Lefebvre's (2006) findings for children in Sweden and Quebec, respectively.

We find that income has a significant impact on the probability of being in poor health. In addition, our results indicate that chronic conditions and activity limitations have large and significant impacts on the probability of a given child being in poor health. These findings are in line with the existing literature.

Lefebvre (2006) finds that effect of chronic conditions does not vary by income levels when working with data from Quebec, contrary to Case et al. (2002). We can confirm, in part, his findings. However, we find a differential income effect for asthma and mental handicap, which was also found by Case et al. (2002). For asthma, the interaction coefficient is negative, suggesting that low-income children are more adversely affected by this chronic condition than their high-income counterparts. Conversely, for mental handicap we find the differential income effect to be quite large and positive[13]. This finding does not support the hypothesis that income (or parental characteritics associated with income) protects children from the adverse effects of mental handicap. Thus, it would seem that children from wealthier families are in

[13]This is not in line with Case et al.'s (2002) findings.

worse health for this condition only.

Case et al. (2002) found that the protective impact of income increases as children age. Our results do not support this hypothesis. When we estimate the β_3 coefficients for younger and older children, we find that these are rarely statistically siginficant and, if so, only for younger children.

Furthermore, we find that our income-health elasticities are quite small when compared to those found in the literature (Blau, 1999). In other words, we find that the impact of income on the improvement of children's chronic health conditions is quite small. Thus, our results suggest that cash transfers and/or income-based services may not be the most efficient solution to impact child health and that it would require substantially large income transfers to low-income families to improve children's general health. Finally, we also confirm the greater role played by maternal characteristics in explaining both the prevalence of child chronic conditions as well as child general health.

In general, we find for most health conditions Canadian children from poor families are no more likely to experience ill health than children from rich families. However, these findings cannot rule out the possibility that richer children are more likely to have their condition diagnosed or to adhere to their treatment programs.

Some of the limitations encountered in our work are mainly related to sample size issues with the NLSCY data. For example, the NLSCY sample is too small to examine how rare childhood conditions, such as epilepsy and cerebral palsy, are related to health status. Furthermore, the NLSCY does not have data on chronic conditions such as diabetes and physical ailments (deformity, hearing and vision problems), which have been found to have a significant impact on child health.

The NLSCY is a longitudinal dataset; however, we do not make use of its panel nature in our analyses. It may prove interesting to examine this topic using panel data models, namely sibling fixed-effects models, to understand whether the income-child health relationship is merely causal or rather a result of unobserved heterogeneity. The literature suggests that the estimated impact of income on child outcomes is small and imprecise (Blau, 1999; Dooley and Stewart, 2004).

Furthermore, the models employed in this paper are of a parametric nature. However, previous research has provided evidence that nonparametric methods may reveal important structure in the data that may not be captured by traditional parametric models (Li and Racine, 2007); future research should address this aspect.

3.7 Conclusion

Previous research has shown that low-income children have poorer health compared to their high-income counterparts. Many researchers have attributed this difference to the impact chronic conditions on child health. Case et al. (2002) find that poor children are more likely than wealthy children to experience some chronic conditions in the US. We examine this issue further within the Canadian context.

We find that, once we control for a series of covariates, which we believe to impact child health, income does not have a protective effect on the prevalence of child chronic conditions. For Canadian children, we find evidence that income plays a role in explaining the prevalence of bronchitis only. Broadly, we can conclude that family income has a protective effect for respiratory conditions only.

Moreover, we find that household income and having a chronic health condition have a siginificant impact on the probability of being in poor health. Contrary to Case et al. (2002), we do not find a differential income effect of chronic health conditions on the probability of being in poor health, with the exception of asthma and mental handicap. Thus, our findings do *not* support the hypothesis that income protects children from the adverse impact of chronic conditions. In addition, we do not find any evidence that this effect is cumulative with age. This suggest that income-related policies, such as cash transfers, may have little or no impact in improving child health, namely child chronic conditions.

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Table 3.1: List of Child Chronic Health Conditions Examined by Study

Authors	Country	Chronic Conditions Analysed
Case et al. (2002)	US	deformity asthma bronchitis fever sinusitis vision problems hearing problems retardation epilepsy diabetes heart disease digestive problem kidney disease frequent headaches
A. Currie et al. (2006) Case et al. (2008)	England	arthritis/rheumatism/fibrositis back problems/spine/neck/other problems of bones/joints/muscles asthma bronchitis/emphysema/other respiratory complaints blindness/deafness/tinnitus/other eye and ear complaints mental illness/mental handicap/epilepsy/other problems of nervous system diabetes (including hyperglycaemia)/other endocrine/metabolic conditions hypertension/high blood pressure/blood pressure related problems cerebral haemorrhage or thrombosis/heart problems digestive system complaints/stomach conditions/abdominal hernia skin complaints other conditions including cancer/kidney complaints
Nahum (2006)	Sweden	asthma allergies impaired vision impaired hearing epilepsy diabetes digestive system complaints skin complaints – psoriasis headache/migraine
Lefebvre (2006)	Canada	asthma allergies bronchitis mental retardation epilepsy heart condition kidney condition other chronic conditions (not specified)

Table 3.2: Summary Statistics

Variable	Mean	Variable	Mean
Asthma	0.126 (0.332)	Age	6.755 (3.896)
Allergies	0.157 (0.364)	Male	0.506 (0.500)
Bronchitis	0.027 (0.162)	White	0.813 (0.390)
Heart condition or disease	0.012 (0.107)	Black	0.005 (0.069)
Epilepsy	0.002 (0.049)	Other	0.184 (0.387)
Cerebral palsy	0.002 (0.040)	Family size	4.269 (1.232)
Kidney condition or disease	0.004 (0.061)	PMK female	0.937 (0.243)
Mental handicap	0.003 (0.058)	Mother's age	27.942 (4.697)
Learning disability	0.003 [a] (0.193)	PMK depression score	4.161 (4.878)
Emotional, psychological or nervous difficulties	0.015 [a] (0.120)	Mother - poor health	0.245 (0.430)
Any other long-term condition	0.039 (0.194)	Father - poor health	0.257 (0.437)
Activity limitations	0.036 (0.186)	Mother - smoking	0.288 (0.453)
Presence of a chronic condition and/or an activity limitation	0.287 (0.452)	Father - smoking	0.340 (0.474)
Household Income ($1998)	57,623 (35,366)	Mother's educ.	2.563 (0.959)
		Father's educ.	2.421 (1.050)
Number of observations	33,025		

Note: Standard errors are shown in brackets.

[a] Information for this chronic condition is available for children ages 6 to 15 only.

Table 3.3: Chronic Conditions, Income, and Poor Health, Replication of Case et al. (2002)

			Model 1		Model 2			
							β_3 for children ages:	
Condition (C)	Sample Size	Fraction with C = 1	α_1	β_1	β_2	β_3	0 – 8	9 – 15
Ages 0-15								
Asthma	41,079	0.1318	**-0.0158**	**-0.0394**	**0.2115**	**-0.0589**	**-0.0683**	-0.0275
			(0.0039)	(0.0030)	(0.0078)	(0.0115)	(0.0146)	(0.0172)
Allergies	41,072	0.1580	**0.0075**	**-0.0409**	**0.1400**	**-0.0267**	-0.0254	-0.0198
			(0.0037)	(0.0066)	(0.0030)	(0.0102)	(0.0135)	(0.0151)
Bronchitis	41,072	0.0289	**-0.0141**	**-0.0385**	**0.2411**	-0.0310	-0.0052	-0.0717
			(0.0017)	(0.0030)	(0.01537)	(0.0236)	(0.0289)	(0.0403)
Heart condition or disease	41,072	0.0116	**-0.0022**	**-0.0399**	**0.1936**	0.0370	0.0027	0.0795
			(0.0011)	(0.0030)	(0.0257)	(0.0415)	(0.05190	(0.0633)
Epilepsy	41,072	0.0030	**-0.0015**	**-0.0398**	**0.3830**	0.0209	-0.0093	0.0949
			(0.0007)	(0.0030)	(0.0577)	(0.0847)	(0.10760	(0.1159)
Cerebral palsy	41,072	0.0019	0.0010	**-0.0405**	**0.2981**	-0.0951	-0.1311	0.0715
			(0.0006)	(0.0030)	(0.0675)	(0.0844)	(0.0898)	(0.1564)
Kidney condition or disease	41,072	0.0041	-0.0007	**-0.0401**	**0.2930**	-0.0823	-0.0806	-0.1206
			(0.0007)	(0.0030)	(0.0467)	(0.0620)	(0.0658)	0.1256)
Mental handicap	41,072	0.0038	0.0003	**-0.0403**	**0.3803**	-0.1170	**0.1715**	0.0261
			(0.0007)	(0.0030)	(0.0513)	(0.0700)	(0.0867)	(0.1202)
Any other long-term condition	41,072	0.0407	-0.0023	**-0.0399**	**0.2339**	-0.0199	-0.0056	-0.0361
			(0.0018)	(0.0030)	(0.0129)	(0.0196)	(0.0256)	(0.0294)
Ages 6-15								
Learning disability	24,218	0.0438	**-0.0114**	**-0.0461**	**0.1681**	0.0016	0.0179	-0.0220?
			(0.0030)	(0.0040)	(0.0169)	(0.0236)	(0.0454)	(0.0271)
Emotional, psychological or nervous difficulties		0.0190	**-0.0096**	**-0.0456**	**0.2606**	-0.0400	-.0248	-0.0466
	24,218		(0.0019)	(0.0040)	(0.0247)	(0.0387)	(0.0624)	(0.0473)

For each regression, observations were clustered by child ID. Robust standard errors are shown in brackets.
Coefficients in bold are statistically significant at the 5% level.

Regression equations are as follows:

Model 1

$$C = \alpha_0 + \alpha_1\ ln(inc) + X\delta^C + \epsilon^C$$

Model 2

$$H = \beta_0 + \beta_1\ [ln(inc) - \overline{ln(inc)}] + \beta_2\ C + \beta_3\ [ln(inc) - \overline{ln(inc)}]\ C + X\delta^C + \epsilon^C$$

C = 1 if the child has the health condition listed in the first column, and is 0 otherwise. H = 1 if the child is in good, fair or poor health, and is 0 otherwise.

All regressions include a complete set of age dummies, year dummies, the natural logarithm of family size, and indicator variables for whether the child is male, white, or black. The last two columns show estimates of β_3 for regressions estimated on separate sample of children aged 0-8 and 9-17.

Table 3.4: Chronic Conditions, Income, and Poor Health, de Oliveira Model

			Model 1	Model 2				
							β_3 for children ages:	
Condition (C)	Sample Size	Fraction with C = 1	α_1	β_1	β_2	β_3	0 − 8	9 − 15
Ages 0-15								
Asthma	33,025	0.1258	0.0067	-0.0045	**0.2036**	**-0.0623**	**-0.0858**	-0.0141
			(0.0050)	(0.0039)	(0.0088)	(0.0143)	(0.0185)	(0.0210)
Allergies	33,025	0.1570	0.0001	**-.01031**	**0.1237**	-0.0042	-0.0062	0.0038
			(0.0052)	(0.0041)	(0.0073)	(0.0123)	(0.0164)	(0.0182)
Bronchitis	33,025	0.0269	**-0.0071**	**-0.0086**	**0.2103**	-0.0282	0.0036	-0.0773
			(0.0023)	(0.0041)	(0.0167)	(0.0294)	(0.0353)	(0.0519)
Heart condition or disease	33,025	0.0115	0.0005	**-0.0114**	**0.1797**	0.0445	0.0076	0.0757
			(0.0015)	(0.0041)	(0.0281)	(0.0500)	(0.0666))	(0.0718)
Epilepsy	33,025	0.0024	-0.0001	**-0.0110**	**0.3795**	0.0378	0.0744	0.0734
			(0.0008)	(0.0041)	(0.0650)	(0.0847)	(0.1131)	(0.1336)
Cerebral palsy	33,025	0.0016	0.0007	**-0.0108**	**0.3071**	-0.1736	**-0.1900**	-0.1068
			(0.0006)	(0.0041)	(0.0768)	(0.0890)	(0.0873)	(0.2164)
Kidney condition or disease	33,025	0.0038	0.0007	**-0.0110**	**0.2665**	-0.0188	0.0036	-0.1565
			(0.0009)	(0.0041)	(0.0499)	(0.0713)	(0.0695)	(0.1620)
Mental handicap	33,025	0.0033	-0.0010	**-0.0112**	**0.3459**	**0.2378**	**0.2996**	0.1022
			(0.0009)	(0.0041)	(0.0555)	(0.0939)	(0.1209)	(0.1668)
Any other long-term condition	33,025	0.0390	-0.0021	**-0.0105**	**0.2193**	0.0019	0.0221	-0.0257
			(0.0025)	(0.0040)	(0.0144)	(0.0254)	(0.0327)	(0.0383)
Ages 6-15								
Learning disability	19,143	0.0387	0.0008	**-0.0115**	**0.1545**	-0.0055	0.0218	-0.0135
			(0.0040)	(0.0054)	(0.0197)	(0.0307)	(0.0638)	(0.0337)
Emotional, psychological or nervous difficulties	19,143	0.0146	-0.0000	**-0.0118**	**0.2262**	0.0194	0.0857	-0.0086
			(0.0021)	(0.0054)	(0.0299)	(0.0553)	(0.0844)	(0.0713)

Chronic Conditions, Income, and Poor Health, de Oliveira Model (cont.)

Condition (C)	Sample Size	Fraction with C = 1	Model 1	Model 2				
							β_3 for children ages:	
			α_1	β_1	β_2	β_3	0 – 8	9 – 15
Ages 0-15								
Any chronic condition	33,025	0.2510	-0.0018 (0.0099)	-0.0043 (0.0038)	**0.1306** (0.0041)	**-0.0178** (0.0068)	**-0.0178** (0.0087)	-0.0102 (0.0103)
Activity limitations	33,025	0.0359	0.0018 (0.0027)	**-0.0108** (0.0040)	**0.3321** (0.0160)	-0.0350 (0.0253)	-0.0433 (0.0332)	-0.0139 (0.0383)
Any chronic condition and/or activity limitation	33,025	0.2869	-0.0022 (0.0066)	-0.0028 (0.0038)	**0.1661** (0.0056)	**-0.0303** (0.0093)	**-0.0375** (0.0119)	-0.0087 (0.0141)
Heart and/or kidney condition or disease	33,025	0.0150	0.0011 (0.0017)	**-0.0122** (0.0042)	**0.1995** (0.0245)	0.0219 (0.0408)	-0.0025 (0.0485)	0.0471 (0.0669)
Learning disability and/or emotional, psychological or nervous difficulties	33,025	0.0404	0.0029 (0.0038)	**-0.0125** (0.0055)	**0.1640** (0.0188)	-0.0145 (0.0307)	0.0224 (0.0617)	-0.0235 (0.0339)
Other chronic conditions (combined)	33,025	0.0439	-0.0027 (0.0027)	**-0.0109** (0.0041)	**0.2309** (0.0138)	-0.0048 (0.0234)	0.0066 (0.0298)	-0.0204 (0.0370)

For each regression, observations were clustered by child ID. Robust standard errors are shown in brackets. Coefficients in bold are statistically significant at the 5% level.

Regression equations are as follows:

Model 1

$$C = \alpha_0 + \alpha_1 \; ln(inc) + X\delta^C + \epsilon^C$$

Model 2

$$H = \beta_0 + \beta_1 \; [ln(inc) - \overline{ln(inc)}] + \beta_2 \; C + \beta_3 \; [ln(inc) - \overline{ln(inc)}] \; C + X\delta^C + \epsilon^C$$

C = 1 if the child has the health condition listed in the first column, and is 0 otherwise. H = 1 if the child is in good, fair or poor health, and is 0 otherwise.

All regressions include a complete set of age dummies, the natural logarithm of family size, the mother's age at the child's birth; the PMK's depression score; parents' education, and indicator variables for whether the child is male, white; whether the PMK is female; whether the mother and father are in poor health and whether the mother and father smoke. The last two columns show estimates of β_3 for regressions estimated on separate sample of children aged 0-8 and 9-17.

Table 3.5: Chronic Conditions, Income, and Poor Health, Case et al. (2002) Replic. (de Oliv. Sample)

			Model 1	Model 2				
							β_3 for children ages:	
Condition (C)	Sample Size	Fraction with C = 1	α_1	β_1	β_2	β_3	0 – 8	9 – 15
Ages 0-15								
Asthma	33,025	0.1258	-0.0082	**-0.0388**	**0.2180**	**-0.0747**	**-0.0950**	-0.0302
			(0.0047)	(0.0036)	(0.0092)	(0.0151)	(0.0194)	(0.0223)
Allergies	33,025	0.1570	0.0023	**-0.0485**	**0.1347**	-0.0134	-0.0081	-0.0140
			(0.0046)	(0.0038)	(0.0077)	(0.0130)	(0.0174)	(0.0191)
Bronchitis	33,025	0.269	**-0.0155**	**-0.0453**	**0.2378**	-0.0390	-0.0035	-0.0956
			(0.0021)	(0.0038)	(0.0172)	(0.0310)	(0.03710	(0.0539)
Heart condition or disease	33,025	0.0115	-0.0022	**-0.0501**	**0.1940**	0.0380	0.0158	0.0577
			(0.0014)	(0.0039)	(0.0287)	(0.0527)	(0.0672)	(0.0787)
Epilepsy	33,025	0.0024	-0.0008	**-0.0498**	**0.4247**	0.0093	0.0346	0.0250
			(0.0007)	(0.0039)	(0.0680)	(0.0936)	(0.1175)	(0.1612)
Cerebral palsy	33,025	0.0016	0.0007	**-0.0500**	**0.3156**	**-0.1743**	**-0.1976**	-0.0713
			(0.0007)	(0.0039)	(0.0772)	(0.0858)	(0.0793)	(0.2326)
Kidney condition or disease	33,025	0.0038	-0.0000	**-0.0500**	**0.2887**	-0.0387	-0.0176	-0.1827
			(0.0008)	(0.0039)	(0.0529)	(0.0756)	(0.0709)	(0.1818)
Mental handicap	33,025	0.0033	-0.0007	**-0.0504**	**0.3555**	0.2001	**0.2710**	0.0493
			(0.0007)	(0.0039)	(0.0584)	(0.1031)	(0.1310)	(0.1939)
Any other long-term condition	33,025	0.0390	-0.0038	**-0.0492**	**0.2329**	-0.0030	0.0223	-0.0411
			(0.0022)	(0.0038)	(0.0149)	(0.0262)	(0.0338)	(0.0392)
Ages 6-15								
Learning disability	19,143	0.0387	**-0.0077**	**-0.0532**	**0.1839**	-0.0138	0.0158	-0.0216
			(0.0036)	(0.0050)	(0.0210)	(0.0331)	(0.0672)	(0.0367)
Emotional, psychological or nervous difficulties	19,143	0.0146	**-0.0042**	**-0.0538**	**0.2797**	-0.0128	0.0401	-0.0357
			(0.0020)	(0.0051)	(0.0319)	(0.0600)	(0.0916)	(0.0779)

For each regression, observations were clustered by child ID. Robust standard errors are shown in brackets. Coefficients in bold are statistically significant at the 5% level.

Regression equations are as follows:

Model 1

$$C = \alpha_0 + \alpha_1\ ln(inc) + X\delta^C + \epsilon^C$$

Model 2

$$H = \beta_0 + \beta_1\ [ln(inc) - \overline{ln(inc)}] + \beta_2\ C + \beta_3\ [ln(inc) - \overline{ln(inc)}]\ C + X\delta^C + \epsilon^C$$

C = 1 if the child has the health condition listed in the first column, and is 0 otherwise. H = 1 if the child is in good, fair or poor health, and is 0 otherwise.

All regressions include a complete set of age dummies, year dummies, the natural logarithm of family size, and indicator variables for whether the child is male, white, or black. The last two columns show estimates of β_3 for regressions estimated on separate sample of children aged 0-8 and 9-17.

APPENDIX

Regressions for the de Oliveira model are included in their entirety in this section. For all regressions, robust standard errors are shown in brackets. Coefficients in bold are statistically significant at the 5% level.

Table 3.6: Model 1 for Asthma - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	0.0067 (0.0050)	White	0.0058 (0.0067)
Age 1 Dummy	**0.0392** (0.0076)	Log of family size	**-0.0599** (0.0120)
Age 2 Dummy	**0.0597** (0.0062)	Male	**0.0470** (0.0053)
Age 3 Dummy	**0.0715** (0.0074)	PMK female	0.0035 (0.0088)
Age 4 Dummy	**0.0964** (0.0066)	Mother's age at child birth	**-0.0020** (0.0006)
Age 5 Dummy	**0.1098** (0.0077)	PMK depression score	**0.0018** (0.0005)
Age 6 Dummy	**0.1148** (0.0079)	Mother - poor health	**0.0334** (0.0056)
Age 7 Dummy	**0.1239** (0.0086)	Father - poor health	**0.0040** (0.0053)
Age 8 Dummy	**0.1327** (0.0086)	Mother - smoking	-0.0016 (0.0064)
Age 9 Dummy	**0.1381** (0.0091)	Father - smoking	**0.0123** (0.0061)
Age 10 Dummy	**0.1483** (0.0090)	Mother's educ. - 2	-0.0114 (0.0089)
Age 11 Dummy	**0.1272** (0.0091)	Mother's educ. - 3	0.0022 (0.0083)
Age 12 Dummy	**0.1272** (0.0103)	Mother's educ. - 4	0.0064 (0.0113)
Age 13 Dummy	**0.1436** (0.0109)	Father's educ. - 2	-0.0155 (0.0083)
Age 14 Dummy	**0.1305** (0.0131)	Father's educ. - 3	-0.0036 (0.0074)
Age 15 Dummy	**0.1260** (0.0149)	Father's educ. - 4	-0.0166 (0.0100)
		Constant	0.0461 (0.0566)
R^2	0.0235	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.7: Model 1 for Allergies - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	0.0001	White	-0.0071
	(0.0052)		(0.0069)
Age 1 Dummy	**0.0541**	Log of family size	**-0.0909**
	(0.0089)		(0.0125)
Age 2 Dummy	**0.0621**	Male	**0.0200**
	(0.0070)		(0.0054)
Age 3 Dummy	**0.0737**	PMK female	**0.0340**
	(0.0080)		(0.0085)
Age 4 Dummy	**0.0953**	Mother's age at child birth	-0.0004
	(0.0072)		(0.0006)
Age 5 Dummy	**0.1250**	PMK depression score	**0.0015**
	(0.0085)		(0.0005)
Age 6 Dummy	**0.1359**	Mother - poor health	**0.0412**
	(0.0087)		(0.0060)
Age 7 Dummy	**0.1528**	Father - poor health	-0.0004
	(0.0095)		(0.0056)
Age 8 Dummy	**0.1616**	Mother - smoking	0.0003
	(0.0094)		(0.0063)
Age 9 Dummy	**0.1773**	Father - smoking	**-0.0047**
	(0.0101)		(0.0060)
Age 10 Dummy	**0.1935**	Mother's educ. - 2	-0.0084
	(0.0099)		(0.0087)
Age 11 Dummy	**0.1894**	Mother's educ. - 3	0.0154
	(0.0104)		(0.0080)
Age 12 Dummy	**0.1954**	Mother's educ. - 4	0.0197
	(0.0116)		(0.0114)
Age 13 Dummy	**0.1960**	Father's educ. - 2	0.0030
	(0.0125)		(0.0082)
Age 14 Dummy	**0.2160**	Father's educ. - 3	0.0131
	(0.0156)		(0.0072)
Age 15 Dummy	**0.1973**	Father's educ. - 4	0.0144
	(0.0176)		(0.0103)
		Constant	0.0991
			(0.0578)
R^2	0.0284	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.8: Model 1 for Bronchitis - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0071** (0.0023)	White	**0.0058** (0.0026)
Age 1 Dummy	**0.0182** (0.0056)	Log of family size	**-0.0166** (0.0048)
Age 2 Dummy	**0.0108** (0.0040)	Male	**0.0071** (0.0021)
Age 3 Dummy	0.0066 (0.0044)	PMK female	0.0001 (0.0038)
Age 4 Dummy	**0.0140** (0.0041)	Mother's age at child birth	-0.0005 (0.0003)
Age 5 Dummy	**0.0149** (0.0046)	PMK depression score	**0.0009** (0.0003)
Age 6 Dummy	**0.0220** (0.0048)	Mother - poor health	**0.0110** (0.0028)
Age 7 Dummy	**0.0159** (0.0048)	Father - poor health	0.0033 (0.0025)
Age 8 Dummy	**0.0194** (0.0048)	Mother - smoking	0.0045 (0.0028)
Age 9 Dummy	**0.0119** (0.0048)	Father - smoking	**0.0065** (0.0026)
Age 10 Dummy	**0.0193** (0.0049)	Mother's educ. - 2	**-0.0225** (0.0041)
Age 11 Dummy	**0.0159** (0.0050)	Mother's educ. - 3	**-0.0199** (0.0039)
Age 12 Dummy	**0.0176** (0.0055)	Mother's educ. - 4	**-0.0173** (0.0046)
Age 13 Dummy	**0.0152** (0.0057)	Father's educ. - 2	0.0063 (0.0035)
Age 14 Dummy	0.0085 (0.0061)	Father's educ. - 3	0.0052 (0.0030)
Age 15 Dummy	0.0081 (0.0068)	Father's educ. - 4	0.0033 (0.0036)
		Constant	0.1215 (0.0265)
R^2	0.0114	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.9: Model 1 for Heart Condition or Disease - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	0.0005 (0.0015)	White	0.0010 (0.0020)
Age 1 Dummy	0.0008 (0.0033)	Log of family size	-0.0021 (0.0039)
Age 2 Dummy	0.0008 (0.0025)	Male	0.0009 (0.0017)
Age 3 Dummy	0.0040 (0.0033)	PMK female	**0.0070** (0.0016)
Age 4 Dummy	0.0026 (0.0027)	Mother's age at child birth	0.0004 (0.0002)
Age 5 Dummy	0.0034 (0.0032)	PMK depression score	0.0003 (0.0002)
Age 6 Dummy	0.0037 (0.0032)	Mother - poor health	0.0037 (0.0021)
Age 7 Dummy	0.0037 (0.0033)	Father - poor health	**-0.0037** (0.0017)
Age 8 Dummy	0.0047 (0.0033)	Mother - smoking	0.0013 (0.0022)
Age 9 Dummy	0.0052 (0.0035)	Father - smoking	0.0020 (0.0019)
Age 10 Dummy	**0.0087** (0.0036)	Mother's educ. - 2	-0.0022 (0.0031)
Age 11 Dummy	0.0043 (0.0036)	Mother's educ. - 3	-0.0004 (0.0030)
Age 12 Dummy	0.0071 (0.0039)	Mother's educ. - 4	-0.0022 (0.0036)
Age 13 Dummy	**0.0086** (0.0043)	Father's educ. - 2	-0.0039 (0.0028)
Age 14 Dummy	0.0095 (0.0051)	Father's educ. - 3	**0.0065** (0.0024)
Age 15 Dummy	0.0188 (0.0068)	Father's educ. - 4	**-0.0086** (0.0036)
		Constant	-0.0110 (0.0156)
R^2	0.0032	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.10: Model 1 for Epilepsy - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	-0.0001 (0.0008)	White	**0.0018** (0.0008)
Age 1 Dummy	0.0007 (0.0012)	Log of family size	-0.0021 (0.0014)
Age 2 Dummy	0.0001 (0.0009)	Male	-0.0007 (0.0008)
Age 3 Dummy	-0.0003 (0.0009)	PMK female	0.0013 (0.0007)
Age 4 Dummy	0.0013 (0.0010)	Mother's age at child birth	-0.0000 (0.0001)
Age 5 Dummy	0.0010 (0.0011)	PMK depression score	0.0002 (0.0001)
Age 6 Dummy	**0.0028** (0.0013)	Mother - poor health	0.0010 (0.0009)
Age 7 Dummy	0.0014 (0.0013)	Father - poor health	0.0014 (0.0010)
Age 8 Dummy	0.0016 (0.0012)	Mother - smoking	-0.0002 (0.0008)
Age 9 Dummy	0.0010 (0.0012)	Father - smoking	0.0011 (0.0008)
Age 10 Dummy	0.0024 (0.0013)	Mother's educ. - 2	-0.0026 (0.0015)
Age 11 Dummy	**0.0034** (0.0016)	Mother's educ. - 3	-0.0014 (0.0015)
Age 12 Dummy	**0.0035** (0.0018)	Mother's educ. - 4	-0.0014 (0.0017)
Age 13 Dummy	0.0035 (0.0019)	Father's educ. - 2	0.0018 (0.0014)
Age 14 Dummy	0.0050 (0.0026)	Father's educ. - 3	0.0008 (0.0011)
Age 15 Dummy	0.0023 (0.0023)	Father's educ. - 4	0.0012 (0.0013)
		Constant	-0.0000 (0.0080)
R^2	0.0023	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.11: Model 1 for Cerebral Palsy - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	0.0007 (0.0006)	White	0.0005 (0.0008)
Age 1 Dummy	0.0021 (0.0012)	Log of family size	-0.0019 (0.0020)
Age 2 Dummy	**0.0017** (0.0008)	Male	**0.0016** (0.0007)
Age 3 Dummy	0.0014 (0.0007)	PMK female	**0.0013** (0.0006)
Age 4 Dummy	**0.0018** (0.0001)	Mother's age at child birth	0.0000 (0.0001)
Age 5 Dummy	**0.0026** (0.0000)	PMK depression score	-0.0001 (0.0001)
Age 6 Dummy	**0.0026** (0.0010)	Mother - poor health	0.0002 (0.0007)
Age 7 Dummy	0.0014 (0.0009)	Father - poor health	0.0006 (0.0007)
Age 8 Dummy	**0.0025** (0.0010)	Mother - smoking	-0.0006 (0.0080)
Age 9 Dummy	**0.0025** (0.0011)	Father - smoking	-0.0001 (0.0008)
Age 10 Dummy	**0.0018** (0.0008)	Mother's educ. - 2	0.0002 (0.0010)
Age 11 Dummy	0.0011 (0.0008)	Mother's educ. - 3	0.0005 (0.0009)
Age 12 Dummy	0.0007 (0.0006)	Mother's educ. - 4	0.0004 (0.0012)
Age 13 Dummy	0.0002 (0.0003)	Father's educ. - 2	0.0006 (0.0010)
Age 14 Dummy	0.0012 (0.0012)	Father's educ. - 3	-0.0000 (0.0007)
Age 15 Dummy	-0.0000 (0.0003)	Father's educ. - 4	-0.0001 (0.0012)
		Constant	-0.0090 (0.0078)
R^2	0.0012	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.12: Model 1 for Kidney Condition or Disease - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	0.0007 (0.0009)	White	0.0006 (0.0010)
Age 1 Dummy	0.0011 (0.0017)	Log of family size	-0.0014 (0.0023)
Age 2 Dummy	0.0006 (0.0012)	Male	-0.0003 (0.0009)
Age 3 Dummy	0.0028 (0.0017)	PMK female	-0.0004 (0.0014)
Age 4 Dummy	0.0020 (0.0001)	Mother's age at child birth	0.0001 (0.0001)
Age 5 Dummy	**0.0037** (0.0017)	PMK depression score	0.0001 (0.0001)
Age 6 Dummy	0.0030 (0.0016)	Mother - poor health	0.0004 (0.0009)
Age 7 Dummy	**0.0040** (0.0018)	Father - poor health	0.0011 (0.0010)
Age 8 Dummy	0.0031 (0.0017)	Mother - smoking	0.0005 (0.0011)
Age 9 Dummy	0.0016 (0.0015)	Father - smoking	-0.0005 (0.0010)
Age 10 Dummy	0.0033 (0.0017)	Mother's educ. - 2	0.0023 (0.0017)
Age 11 Dummy	0.0022 (0.0016)	Mother's educ. - 3	0.0013 (0.0013)
Age 12 Dummy	0.0002 (0.0014)	Mother's educ. - 4	0.0013 (0.0018)
Age 13 Dummy	0.0013 (0.0018)	Father's educ. - 2	-0.0028 (0.0016)
Age 14 Dummy	0.0018 (0.0023)	Father's educ. - 3	**-0.0033** (0.0014)
Age 15 Dummy	-0.0002 (0.0019)	Father's educ. - 4	-0.0031 (0.0017)
		Constant	-0.0056 (0.0103)
R^2	0.0012	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.13: Model 1 for Mental Handicap - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	-0.0010 (0.0009)	White	0.0011 (0.0010)
Age 1 Dummy	0.0000 (0.0014)	Log of family size	-0.0017 (0.0021)
Age 2 Dummy	0.0020 (0.0011)	Male	0.0016 (0.0009)
Age 3 Dummy	0.0010 (0.0014)	PMK female	0.0007 (0.0014)
Age 4 Dummy	**0.0034** (0.0013)	Mother's age at child birth	**0.0003** (0.0001)
Age 5 Dummy	**0.0019** (0.0015)	PMK depression score	**0.0003** (0.0001)
Age 6 Dummy	0.0024 (0.0016)	Mother - poor health	-0.0013 (0.0010)
Age 7 Dummy	0.0024 (0.0016)	Father - poor health	0.0005 (0.0008)
Age 8 Dummy	0.0030 (0.0016)	Mother - smoking	-0.0009 (0.0013)
Age 9 Dummy	0.0027 (0.0016)	Father - smoking	0.0018 (0.0011)
Age 10 Dummy	0.0032 (0.0017)	Mother's educ. - 2	-0.0024 (0.0016)
Age 11 Dummy	0.0025 (0.0017)	Mother's educ. - 3	-0.0008 (0.0016)
Age 12 Dummy	0.0046 (0.0022)	Mother's educ. - 4	0.0009 (0.0021)
Age 13 Dummy	0.0028 (0.0019)	Father's educ. - 2	0.0013 (0.0016)
Age 14 Dummy	**0.0104** (0.0039)	Father's educ. - 3	-0.0005 (0.0011)
Age 15 Dummy	0.0031 (0.0026)	Father's educ. - 4	-0.0005 (0.0015)
		Constant	0.0023 (0.0090)
R^2	0.0025	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.14: Model 1 for Learning Disability - de Oliveira

Chronic condition available for children 6-15 only.

Variable	Coefficient	Variable	Coefficient
Ln income	0.0008 (0.0040)	White	0.0022 (0.0048)
		Log of family size	0.0019 (0.0095)
		Male	**0.0296** (0.0038)
		PMK female	**0.0185** (0.0055)
		Mother's age at child birth	0.0003 (0.0005)
		PMK depression score	**0.0022** (0.0004)
		Mother - poor health	**-0.0114** (0.0043)
Age 6 Dummy	**-0.0326** (0.0093)	Father - poor health	0.0052 (0.0040)
Age 7 Dummy	**-0.0245** (0.0095)	Mother - smoking	**-0.0116** (0.0047)
Age 8 Dummy	**-0.0199** (0.0096)	Father - smoking	-0.0004 (0.0043)
Age 9 Dummy	-0.0166 (0.0098)	Mother's educ. - 2	-0.0090 (0.0066)
Age 10 Dummy	-0.0035 (0.0099)	Mother's educ. - 3	-0.0113 (0.0063)
Age 11 Dummy	-0.0056 (0.0088)	Mother's educ. - 4	-0.0090 (0.0084)
Age 12 Dummy	-0.0033 (0.0103)	Father's educ. - 2	-0.0048 (0.0057)
Age 13 Dummy	0.0043 (0.0082)	Father's educ. - 3	0.0033 (0.0054)
Age 14 Dummy	0.0103 (0.0121)	Father's educ. - 4	0.0008 (0.0073)
		Constant	-0.0124 (0.0464)
R^2	0.0185	No. observations	19,143

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.15: Model 1 for Emotional, Psych. or Nervous Difficulties - de Oliveira

Chronic condition available for children 6-15 only.

Variable	**Coefficient**	**Variable**	**Coefficient**
Ln income	-0.0000 (0.0021)	White	-0.0019 (0.0029)
		Log of family size	-0.0002 (0.0056)
		Male	**0.0064** (0.0022)
		PMK female	**0.0075** (0.0031)
		Mother's age at child birth	-0.0003 (0.0003)
		PMK depression score	**0.0013** (0.0003)
		Mother - poor health	**-0.0134** (0.0028)
Age 6 Dummy	-0.0074 (0.0057)	Father - poor health	0.0013 (0.0022)
Age 7 Dummy	-0.0071 (0.0057)	Mother - smoking	0.0027 (0.0028)
Age 8 Dummy	-0.0001 (0.0059)	Father - smoking	0.0023 (0.0024)
Age 9 Dummy	-0.0040 (0.0058)	Mother's educ. - 2	-0.0009 (0.0037)
Age 10 Dummy	-0.0009 (0.0059)	Mother's educ. - 3	0.0003 (0.0035)
Age 11 Dummy	-0.0015 (0.0054)	Mother's educ. - 4	-0.0014 (0.0044)
Age 12 Dummy	-0.0058 (0.0065)	Father's educ. - 2	0.0015 (0.0034)
Age 13 Dummy	-0.0055 (0.0053)	Father's educ. - 3	0.0031 (0.0029)
Age 14 Dummy	0.0033 (0.0072)	Father's educ. - 4	0.0046 (0.0043)
		Constant	0.0040 (0.0252)
R^2	0.0102	No. observations	19,143

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.16: Model 1 for Any Other Long-term Conditions - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	-0.0021 (0.0025)	White	-0.0060 (0.0034)
Age 1 Dummy	0.0115 (0.0059)	Log of family size	-0.0088 (0.0059)
Age 2 Dummy	0.0088 (0.0048)	Male	**0.0079** (0.0024)
Age 3 Dummy	**0.0126** (0.0053)	PMK female	**0.0096** (0.0042)
Age 4 Dummy	**0.0091** (0.0046)	Mother's age at child birth	-0.0001 (0.0003)
Age 5 Dummy	**0.0165** (0.0003)	PMK depression score	**0.0010** (0.0001)
Age 6 Dummy	**0.0245** (0.0054)	Mother - poor health	**0.0071** (0.0030)
Age 7 Dummy	**0.0339** (0.0060)	Father - poor health	0.0035 (0.0028)
Age 8 Dummy	**0.0226** (0.0056)	Mother - smoking	0.0047 (0.0030)
Age 9 Dummy	**0.0287** (0.0059)	Father - smoking	-0.0023 (0.0028)
Age 10 Dummy	**0.0302** (0.0059)	Mother's educ. - 2	-0.0039 (0.0040)
Age 11 Dummy	**0.0258** (0.0060)	Mother's educ. - 3	0.0024 (0.0037)
Age 12 Dummy	**0.0223** (0.0062)	Mother's educ. - 4	0.0007 (0.0051)
Age 13 Dummy	**0.0350** (0.0073)	Father's educ. - 2	-0.0027 (0.0038)
Age 14 Dummy	**0.0280** (0.0081)	Father's educ. - 3	-0.0003 (0.0033)
Age 15 Dummy	**0.0262** (0.0092)	Father's educ. - 4	0.0015 (0.0047)
		Constant	0.0407 (0.0280)
R^2	0.0047	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.17: Model 1 for Any Chronic Condition - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	-0.0018 (0.0099)	White	0.0034 (0.0128)
Age 1 Dummy	**0.1277** (0.0168)	Log of family size	**-0.1833** (0.0239)
Age 2 Dummy	**0.1466** (0.0126)	Male	**0.0851** (0.0104)
Age 3 Dummy	**0.1733** (0.0155)	PMK female	**0.0572** (0.0157)
Age 4 Dummy	**0.2259** (0.0134)	Mother's age at child birth	-0.0023 (0.0012)
Age 5 Dummy	**0.2787** (0.0161)	PMK depression score	**0.0050** (0.0010)
Age 6 Dummy	**0.3116** (0.0164)	Mother - poor health	**0.0967** (0.00118)
Age 7 Dummy	**0.3394** (0.0176)	Father - poor health	0.0104 (0.0107)
Age 8 Dummy	**0.3512** (0.0176)	Mother - smoking	0.0093 (0.0124)
Age 9 Dummy	**0.3691** (0.0184)	Father - smoking	0.0160 (0.0116)
Age 10 Dummy	**0.4107** (0.0189)	Mother's educ. - 2	**-0.0507** (0.0176)
Age 11 Dummy	**0.3718** (0.0191)	Mother's educ. - 3	-0.0007 (0.0163)
Age 12 Dummy	**0.3950** (0.0210)	Mother's educ. - 4	0.0086 (0.0225)
Age 13 Dummy	**0.3930** (0.0226)	Father's educ. - 2	-0.0118 (0.0164)
Age 14 Dummy	**0.4063** (0.0286)	Father's educ. - 3	0.0048 (0.0141)
Age 15 Dummy	**0.3720** (0.0309)	Father's educ. - 4	-0.0086 (0.0196)
		Constant	**-0.2840** (0.1118)
R^2	0.0398	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.18: Model 1 for Activity Limitations - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	0.0018 (0.0027)	White	-0.0063 (0.0034)
Age 1 Dummy	**0.0135** (0.0048)	Log of family size	-0.0081 (0.0061)
Age 2 Dummy	**0.0087** (0.0034)	Male	**0.0055** (0.0025)
Age 3 Dummy	**0.0081** (0.0039)	PMK female	**0.0102** (0.0039)
Age 4 Dummy	**0.0130** (0.0036)	Mother's age at child birth	0.0001 (0.0003)
Age 5 Dummy	**0.0206** (0.0043)	PMK depression score	**0.0023** (0.0003)
Age 6 Dummy	**0.0258** (0.0045)	Mother - poor health	**0.0169** (0.0032)
Age 7 Dummy	**0.0256** (0.0048)	Father - poor health	**0.0061** (0.0029)
Age 8 Dummy	**0.0325** (0.0050)	Mother - smoking	**0.0066** (0.0032)
Age 9 Dummy	**0.0329** (0.0052)	Father - smoking	0.0002 (0.0029)
Age 10 Dummy	**0.0414** (0.0053)	Mother's educ. - 2	-0.0045 (0.0044)
Age 11 Dummy	**0.0392** (0.0055)	Mother's educ. - 3	0.0011 (0.0042)
Age 12 Dummy	**0.0456** (0.0063)	Mother's educ. - 4	0.0020 (0.0055)
Age 13 Dummy	**0.0386** (0.0065)	Father's educ. - 2	0.0012 (0.0041)
Age 14 Dummy	**0.0733** (0.0099)	Father's educ. - 3	-0.0027 (0.0036)
Age 15 Dummy	**0.0571** (0.0104)	Father's educ. - 4	-0.0029 (0.0047)
		Constant	-0.0231 (0.0282)
R^2	0.0156	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.19: Model 1 for Any Chronic Cond. and/or Act. Limit. - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	-0.0022 (0.0066)	White	-0.0077 (0.0086)
Age 1 Dummy	**0.0944** (0.0130)	Log of family size	**-0.1241** (0.0061)
Age 2 Dummy	**0.1079** (0.0102)	Male	**0.0523** (0.0067)
Age 3 Dummy	**0.1182** (0.0117)	PMK female	**0.0280** (0.0112)
Age 4 Dummy	**0.1607** (0.0103)	Mother's age at child birth	-0.0013 (0.0008)
Age 5 Dummy	**0.1926** (0.0118)	PMK depression score	**0.0041** (0.0006)
Age 6 Dummy	**0.2293** (0.0121)	Mother - poor health	**0.0567** (0.0073)
Age 7 Dummy	**0.2445** (0.0128)	Father - poor health	0.0017 (0.0069)
Age 8 Dummy	**0.2452** (0.0126)	Mother - smoking	0.0053 (0.0080)
Age 9 Dummy	**0.2697** (0.0133)	Father - smoking	0.0120 (0.0076)
Age 10 Dummy	**0.2830** (0.0129)	Mother's educ. - 2	**-0.0286** (0.0111)
Age 11 Dummy	**0.2656** (0.0134)	Mother's educ. - 3	0.0062 (0.0103)
Age 12 Dummy	**0.2779** (0.0146)	Mother's educ. - 4	0.0090 (0.0141)
Age 13 Dummy	**0.2830** (0.0156)	Father's educ. - 2	-0.0129 (0.0104)
Age 14 Dummy	**0.2901** (0.0186)	Father's educ. - 3	0.0033 (0.0091)
Age 15 Dummy	**0.2815** (0.0212)	Father's educ. - 4	-0.0099 (0.0127)
		Constant	**0.2435** (0.0730)
R^2	0.0402	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.20: Model 1 for Heart and/or Kidney Condition or Disease - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	0.0011 (0.0017)	White	0.0014 (0.0022)
Age 1 Dummy	0.0019 (0.0037)	Log of family size	-0.0033 (0.0045)
Age 2 Dummy	0.0014 (0.0028)	Male	0.0008 (0.0019)
Age 3 Dummy	0.0063 (0.0037)	PMK female	**0.0064** (0.0021)
Age 4 Dummy	0.0046 (0.0030)	Mother's age at child birth	**0.0005** (0.0002)
Age 5 Dummy	0.0067 (0.0036)	PMK depression score	**0.0005** (0.0002)
Age 6 Dummy	0.0064 (0.0036)	Mother - poor health	0.0042 (0.0023)
Age 7 Dummy	**0.0078** (0.0038)	Father - poor health	-0.0023 (0.0020)
Age 8 Dummy	**0.0074** (0.0037)	Mother - smoking	0.0021 (0.0024)
Age 9 Dummy	0.0067 (0.0038)	Father - smoking	0.0017 (0.0022)
Age 10 Dummy	**0.0112** (0.0040)	Mother's educ. - 2	-0.0003 (0.0035)
Age 11 Dummy	0.0064 (0.0039)	Mother's educ. - 3	0.0006 (0.0032)
Age 12 Dummy	0.0067 (0.0041)	Mother's educ. - 4	-0.0012 (0.0040)
Age 13 Dummy	**0.0099** (0.0046)	Father's educ. - 2	-0.0061 (0.0032)
Age 14 Dummy	**0.0113** (0.0055)	Father's educ. - 3	**-0.0095** (0.0027)
Age 15 Dummy	**0.0186** (0.0070)	Father's educ. - 4	**-0.0111** (0.0032)
		Constant	-0.0158 (0.0185)
R^2	0.0033	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.
Coefficients in bold are statistically significant at the 5% level.

Table 3.21: Model 1 for Learn. Disab. and/or Emo., Psych. or Nerv. Diff. - de Oliveira

Chronic condition available for children 6-15 only.

Variable	Coefficient	Variable	Coefficient
Ln income	0.0029 (0.0038)	White	0.0006 (0.0045)
		Log of family size	0.0013 (0.0088)
		Male	**0.0266** (0.0036)
		PMK female	**0.0188** (0.0056)
		Mother's age at child birth	-0.0000 (0.0004)
		PMK depression score	**0.0029** (0.0005)
		Mother - poor health	**-0.0204** (0.0043)
Age 6 Dummy	**-0.0407** (0.0100)	Father - poor health	0.0038 (0.0039)
Age 7 Dummy	**-0.0357** (0.0045)	Mother - smoking	**0.0098** (0.0028)
Age 8 Dummy	**-0.0264** (0.0103)	Father - smoking	0.0014 (0.0040)
Age 9 Dummy	**-0.0263** (0.0104)	Mother's educ. - 2	-0.0059 (0.0061)
Age 10 Dummy	-0.0151 (0.0105)	Mother's educ. - 3	-0.0055 (0.0058)
Age 11 Dummy	-0.0187 (0.0103)	Mother's educ. - 4	-0.0060 (0.0076)
Age 12 Dummy	-0.0001 (0.0113)	Father's educ. - 2	-0.0033 (0.0054)
Age 13 Dummy	0.0007 (0.0092)	Father's educ. - 3	0.0048 (0.0049)
Age 14 Dummy	0.0087 (0.0129)	Father's educ. - 4	0.0027 (0.0069)
		Constant	-0.0221 (0.0440)
R^2	0.0226	No. observations	19,143

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.22: Model 1 for Other Chronic Conditions (combined) - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	-0.0027 (0.0027)	White	-0.0042 (0.0036)
Age 1 Dummy	**0.0129** (0.0062)	Log of family size	-0.0119 (0.0066)
Age 2 Dummy	**0.0109** (0.0050)	Male	**0.0096** (0.0027)
Age 3 Dummy	**0.0142** (0.0055)	PMK female	**0.0120** (0.0044)
Age 4 Dummy	**0.0129** (0.0049)	Mother's age at child birth	0.0001 (0.0003)
Age 5 Dummy	**0.0193** (0.0054)	PMK depression score	**0.0013** (0.0003)
Age 6 Dummy	**0.0278** (0.0057)	Mother - poor health	**0.0075** (0.0032)
Age 7 Dummy	**0.0374** (0.0063)	Father - poor health	0.0055 (0.0031)
Age 8 Dummy	**0.0262** (0.0059)	Mother - smoking	0.0050 (0.0033)
Age 9 Dummy	**0.0315** (0.0062)	Father - smoking	-0.0010 (0.0031)
Age 10 Dummy	**0.0328** (0.0061)	Mother's educ. - 2	-0.0071 (0.0044)
Age 11 Dummy	**0.0305** (0.0063)	Mother's educ. - 3	0.0011 (0.0043)
Age 12 Dummy	**0.0277** (0.0067)	Mother's educ. - 4	-0.0012 (0.0056)
Age 13 Dummy	**0.0402** (0.0077)	Father's educ. - 2	-0.0013 (0.0043)
Age 14 Dummy	**0.0359** (0.0089)	Father's educ. - 3	0.0008 (0.0036)
Age 15 Dummy	**0.0312** (0.0098)	Father's educ. - 4	0.0030 (0.0050)
		Constant	0.0411 (0.0305)
R^2	0.0057	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.23: Model 2 for Asthma - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	-0.0045 (0.0039)	White	0.0018 (0.0051)
Asthma	**0.2036** (0.0088)	Log of family size	**0.0247** (0.0096)
Asthma*Ln income	**-0.0623** (0.0143)	Male	0.0042 (0.0039)
Age 1 Dummy	**0.0326** (0.0107)	PMK female	0.0129 (0.0073)
Age 2 Dummy	0.0006 (0.0085)	Mother's age at child birth	0.0006 (0.0005)
Age 3 Dummy	0.0143 (0.0093)	PMK depression score	**0.0024** (0.0005)
Age 4 Dummy	0.0083 (0.0085)	Mother - poor health	**0.1256** (0.0055)
Age 5 Dummy	0.0125 (0.0091)	Father - poor health	**0.0906** (0.0052)
Age 6 Dummy	0.0163 (0.0093)	Mother - smoking	**0.0143** (0.0050)
Age 7 Dummy	0.0140 (0.0097)	Father - smoking	-0.0072 (0.0046)
Age 8 Dummy	0.0121 (0.0096)	Mother's educ. - 2	**-0.0187** (0.0070)
Age 9 Dummy	0.0090 (0.0098)	Mother's educ. - 3	**-0.0230** (0.0066)
Age 10 Dummy	-0.0042 (0.0095)	Mother's educ. - 4	**-0.0344** (0.0084)
Age 11 Dummy	0.0009 (0.0099)	Father's educ. - 2	-0.0044 (0.0063)
Age 12 Dummy	-0.0083 (0.0104)	Father's educ. - 3	-0.0084 (0.0055)
Age 13 Dummy	-0.0145 (0.0109)	Father's educ. - 4	-0.0033 (0.0072)
Age 14 Dummy	0.0237 (0.0138)	Constant	-0.0205 (0.0212)
Age 15 Dummy	0.0180 (0.0152)		
R^2	0.1182	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.24: Model 2 for Allergies - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0103** (0.0041)	White	0.0041 (0.0052)
Allergies	**0.1237** (0.0073)	Log of family size	**0.0249** (0.0097)
Allergies*Ln income	-0.0042 (0.0123)	Male	**0.0107** (0.0040)
Age 1 Dummy	**0.0337** (0.0108)	PMK female	0.0067 (0.0073)
Age 2 Dummy	0.0055 (0.0087)	Mother's age at child birth	0.0002 (0.0005)
Age 3 Dummy	**0.0199** (0.0095)	PMK depression score	**0.0026** (0.0005)
Age 4 Dummy	0.0165 (0.0086)	Mother - poor health	**0.1274** (0.0056)
Age 5 Dummy	**0.0190** (0.0093)	Father - poor health	**0.0917** (0.0052)
Age 6 Dummy	**0.0228** (0.0094)	Mother - smoking	**0.0142** (0.0051)
Age 7 Dummy	**0.0197** (0.0098)	Father - smoking	-0.0042 (0.0047)
Age 8 Dummy	0.0184 (0.0097)	Mother's educ. - 2	**-0.0206** (0.0072)
Age 9 Dummy	0.0144 (0.0099)	Mother's educ. - 3	**-0.0251** (0.0067)
Age 10 Dummy	0.0017 (0.0096)	Mother's educ. - 4	**-0.0358** (0.0085)
Age 11 Dummy	0.0024 (0.0099)	Father's educ. - 2	-0.0078 (0.0065)
Age 12 Dummy	-0.0040 (0.0106)	Father's educ. - 3	**-0.0111** (0.0056)
Age 13 Dummy	-0.0129 (0.0109)	Father's educ. - 4	-0.0083 (0.0074)
Age 14 Dummy	0.0219 (0.0139)	Constant	-0.0087 (0.0217)
Age 15 Dummy	0.0170 (0.0152)		
R^2	0.0964	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.25: Model 2 for Bronchitis - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0086** (0.0041)	White	0.0020 (0.0053)
Bronchitis	**0.2103** (0.0167)	Log of family size	0.0172 (0.0097)
Bronchitis*Ln income	-0.0282 (0.0294)	Male	**0.0117** (0.0041)
Age 1 Dummy	**0.0365** (0.0108)	PMK female	0.0110 (0.0073)
Age 2 Dummy	0.0109 (0.0087)	Mother's age at child birth	0.0003 (0.0005)
Age 3 Dummy	**0.0276** (0.0095)	PMK depression score	**0.0026** (0.0005)
Age 4 Dummy	**0.0251** (0.0086)	Mother - poor health	**0.1302** (0.0057)
Age 5 Dummy	**0.0312** (0.0093)	Father - poor health	**0.0909** (0.0053)
Age 6 Dummy	**0.0347** (0.0094)	Mother - smoking	**0.0133** (0.0051)
Age 7 Dummy	**0.01350** (0.0099)	Father - smoking	-0.0062 (0.0047)
Age 8 Dummy	**0.0343** (0.0097)	Mother's educ. - 2	**-0.0167** (0.0073)
Age 9 Dummy	**0.0336** (0.0099)	Mother's educ. - 3	**-0.0188** (0.0068)
Age 10 Dummy	**0.0214** (0.0096)	Mother's educ. - 4	**-0.0296** (0.0086)
Age 11 Dummy	**0.0224** (0.0100)	Father's educ. - 2	-0.0088 (0.0065)
Age 12 Dummy	0.0162 (0.0106)	Father's educ. - 3	**-0.0105** (0.0057)
Age 13 Dummy	0.0079 (0.0110)	Father's educ. - 4	-0.0075 (0.0075)
Age 14 Dummy	**0.0465** (0.0139)	Constant	-0.0064 (0.0217)
Age 15 Dummy	**0.0394** (0.0154)		
R^2	0.0889	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.26: Model 2 for Heart Condition or Disease - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0114** (0.0041)	White	0.0032 (0.0053)
Heart condition or disease	**0.1797** (0.0281)	Log of family size	0.0140 (0.0098)
Heart condition or disease*Ln income	-0.0445 (0.0500)	Male	**0.0129** (0.0041)
Age 1 Dummy	**0.0404** (0.0109)	PMK female	0.0096 (0.0073)
Age 2 Dummy	0.0131 (0.0087)	Mother's age at child birth	0.0001 (0.0005)
Age 3 Dummy	**0.0283** (0.0095)	PMK depression score	**0.0027** (0.0005)
Age 4 Dummy	**0.0279** (0.0086)	Mother - poor health	**0.1322** (0.0057)
Age 5 Dummy	**0.0339** (0.0093)	Father - poor health	**0.0911** (0.0053)
Age 6 Dummy	**0.0391** (0.0095)	Mother - smoking	**0.0144** (0.0052)
Age 7 Dummy	**0.0379** (0.0099)	Father - smoking	-0.0052 (0.0048)
Age 8 Dummy	**0.0377** (0.0097)	Mother's educ. - 2	**-0.0206** (0.0074)
Age 9 Dummy	**0.0354** (0.0099)	Mother's educ. - 3	**-0.0226** (0.0068)
Age 10 Dummy	**0.0241** (0.0097)	Mother's educ. - 4	**-0.0328** (0.0087)
Age 11 Dummy	**0.0251** (0.0100)	Father's educ. - 2	-0.0081 (0.0066)
Age 12 Dummy	0.0188 (0.0106)	Father's educ. - 3	**-0.0098** (0.0058)
Age 13 Dummy	0.0099 (0.0110)	Father's educ. - 4	-0.0071 (0.0076)
Age 14 Dummy	**0.0467** (0.0138)	Constant	0.0042 (0.0219)
Age 15 Dummy	**0.0379** (0.0152)		
R^2	0.0815	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.27: Model 2 for Epilepsy - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0110** (0.0041)	White	0.0026 (0.0053)
Epilepsy	**0.3795** (0.0650)	Log of family size	0.0137 (0.0098)
Epilepsy*Ln income	0.0378 (0.0847)	Male	**0.0134** (0.0041)
Age 1 Dummy	**0.0401** (0.0109)	PMK female	0.0104 (0.0074)
Age 2 Dummy	0.0132 (0.0087)	Mother's age at child birth	0.0002 (0.0005)
Age 3 Dummy	**0.0291** (0.0096)	PMK depression score	**0.0027** (0.0005)
Age 4 Dummy	**0.0280** (0.0086)	Mother - poor health	**0.1318** (0.0057)
Age 5 Dummy	**0.0341** (0.0093)	Father - poor health	**0.0923** (0.0053)
Age 6 Dummy	**0.0386** (0.0095)	Mother - smoking	**0.0140** (0.0052)
Age 7 Dummy	**0.0380** (0.0099)	Father - smoking	-0.0051 (0.0048)
Age 8 Dummy	**0.0378** (0.0097)	Mother's educ. - 2	**-0.0212** (0.0073)
Age 9 Dummy	**0.0358** (0.0100)	Mother's educ. - 3	**-0.0231** (0.0069)
Age 10 Dummy	**0.0247** (0.0097)	Mother's educ. - 4	**-0.0329** (0.0087)
Age 11 Dummy	**0.0245** (0.0100)	Father's educ. - 2	-0.0068 (0.0066)
Age 12 Dummy	0.0187 (0.0106)	Father's educ. - 3	**-0.0084** (0.0058)
Age 13 Dummy	0.0099 (0.0109)	Father's educ. - 4	-0.0051 (0.0076)
Age 14 Dummy	**0.046** (0.0139)	Constant	-0.0046 (0.0218)
Age 15 Dummy	**0.0404** (0.0153)		
R^2	0.0812	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.28: Model 2 for Cerebral Palsy - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0108** (0.0041)	White	0.0033 (0.0053)
Cerebral Palsy	**0.3071** (0.0768)	Log of family size	0.0141 (0.0098)
Cerebral Palsy*Ln income	-0.1736 (0.0890)	Male	**0.0128** (0.0041)
Age 1 Dummy	**0.0398** (0.0109)	PMK female	0.0106 (0.0073)
Age 2 Dummy	0.0128 (0.0087)	Mother's age at child birth	0.0001 (0.0005)
Age 3 Dummy	**0.0285** (0.0096)	PMK depression score	**0.0028** (0.0005)
Age 4 Dummy	**0.0278** (0.0086)	Mother - poor health	**0.1324** (0.0057)
Age 5 Dummy	**0.0338** (0.0093)	Father - poor health	**0.0915** (0.0053)
Age 6 Dummy	**0.0390** (0.0095)	Mother - smoking	**0.0140** (0.0052)
Age 7 Dummy	**0.0381** (0.0099)	Father - smoking	-0.0046 (0.0048)
Age 8 Dummy	**0.0378** (0.0098)	Mother's educ. - 2	**-0.0218** (0.0074)
Age 9 Dummy	**0.0356** (0.0100)	Mother's educ. - 3	**-0.0235** (0.0069)
Age 10 Dummy	**0.0252** (0.0097)	Mother's educ. - 4	**-0.0335** (0.0087)
Age 11 Dummy	**0.0254** (0.0100)	Father's educ. - 2	-0.0076 (0.0066)
Age 12 Dummy	0.0198 (0.0107)	Father's educ. - 3	**-0.0093** (0.0058)
Age 13 Dummy	0.0112 (0.0110)	Father's educ. - 4	-0.0065 (0.0076)
Age 14 Dummy	**0.0480** (0.0139)	Constant	0.0038 (0.0219)
Age 15 Dummy	**0.0412** (0.0153)		
R^2	0.0790	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.
Coefficients in bold are statistically significant at the 5% level.

Table 3.29: Model 2 for Kidney Condition or Disease - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0110** (0.0042)	White	0.0031 (0.0053)
Kidney Condition or Disease	**0.2665** (0.0499)	Log of family size	0.0140 (0.0098)
Kidney Condition or Disease*Ln income	-0.1881 (0.0713)	Male	**0.0132** (0.0041)
Age 1 Dummy	**0.0401** (0.0109)	PMK female	0.0110 (0.0073)
Age 2 Dummy	0.0130 (0.0087)	Mother's age at child birth	0.0001 (0.0005)
Age 3 Dummy	**0.0283** (0.0096)	PMK depression score	**0.0027** (0.0005)
Age 4 Dummy	**0.0277** (0.0086)	Mother - poor health	**0.1324** (0.0057)
Age 5 Dummy	**0.0335** (0.0093)	Father - poor health	**0.0913** (0.0053)
Age 6 Dummy	**0.0388** (0.0095)	Mother - smoking	**0.0141** (0.0052)
Age 7 Dummy	**0.0375** (0.0099)	Father - smoking	-0.0047 (0.0048)
Age 8 Dummy	**0.0376** (0.0098)	Mother's educ. - 2	**-0.0222** (0.0074)
Age 9 Dummy	**0.0358** (0.0096)	Mother's educ. - 3	**-0.0235** (0.0069)
Age 10 Dummy	**0.0247** (0.0097)	Mother's educ. - 4	**-0.0336** (0.0087)
Age 11 Dummy	**0.0252** (0.0100)	Father's educ. - 2	-0.0067 (0.0066)
Age 12 Dummy	0.0200 (0.0106)	Father's educ. - 3	**-0.0086** (0.0058)
Age 13 Dummy	0.0109 (0.0110)	Father's educ. - 4	-0.0058 (0.0076)
Age 14 Dummy	**0.0480** (0.0139)	Constant	0.0032 (0.0219)
Age 15 Dummy	**0.0413** (0.0153)		
R^2	0.0803	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.30: Model 2 for Mental Handicap - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0112** (0.0041)	White	0.0031 (0.0053)
Mental Handicap	**0.3459** (0.0555)	Log of family size	0.0143 (0.0098)
Mental Handicap*Ln income	**0.2378** (0.0939)	Male	**0.0125** (0.0041)
Age 1 Dummy	**0.0406** (0.0109)	PMK female	0.0107 (0.0073)
Age 2 Dummy	0.0123 (0.0087)	Mother's age at child birth	0.0000 (0.0005)
Age 3 Dummy	**0.0288** (0.0095)	PMK depression score	**0.0027** (0.0005)
Age 4 Dummy	**0.0272** (0.0086)	Mother - poor health	**0.1331** (0.0057)
Age 5 Dummy	**0.0339** (0.0093)	Father - poor health	**0.0916** (0.0053)
Age 6 Dummy	**0.0387** (0.0095)	Mother - smoking	**0.0147** (0.0051)
Age 7 Dummy	**0.0380** (0.0099)	Father - smoking	-0.0055 (0.0048)
Age 8 Dummy	**0.0374** (0.0097)	Mother's educ. - 2	**-0.0206** (0.0073)
Age 9 Dummy	**0.0356** (0.0099)	Mother's educ. - 3	**-0.0226** (0.0068)
Age 10 Dummy	**0.0245** (0.0097)	Mother's educ. - 4	**-0.0335** (0.0087)
Age 11 Dummy	**0.0252** (0.0100)	Father's educ. - 2	-0.0079 (0.0066)
Age 12 Dummy	0.0183 (0.0106)	Father's educ. - 3	**-0.0093** (0.0057)
Age 13 Dummy	0.0105 (0.0110)	Father's educ. - 4	-0.0065 (0.0075)
Age 14 Dummy	**0.0488** (0.0138)	Constant	0.0062 (0.0218)
Age 15 Dummy	**0.0402** (0.0152)		
R^2	0.0826	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.31: Model 2 for Learning Disability - de Oliveira

Chronic condition available for children 6-15 only.

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0115** (0.0054)	White	0.0056 (0.0070)
Learning Disability	**0.1545** (0.0197)	Log of family size	-0.0005 (0.0131)
Learning Disability*Ln income	-0.0055 (0.0307)	Male	0.0001 (0.0054)
		PMK female	0.0056 (0.0102)
		Mother's age at child birth	0.0001 (0.0006)
		PMK depression score	**0.0028** (0.0006)
		Mother - poor health	**0.1390** (0.0074)
		Father - poor health	**0.0939** (0.0068)
Age 6 Dummy	0.0036 (0.0146)	Mother - smoking	0.0115 (0.0068)
Age 7 Dummy	0.0014 (0.0149)	Father - smoking	-0.0036 (0.0063)
Age 8 Dummy	0.0004 (0.0148)	Mother's educ. - 2	-0.0139 (0.0092)
Age 9 Dummy	-0.0021 (0.0149)	Mother's educ. - 3	**-0.0185** (0.0085)
Age 10 Dummy	-0.0148 (0.0147)	Mother's educ. - 4	**-0.0373** (0.0113)
Age 11 Dummy	-0.0142 (0.0139)	Father's educ. - 2	-0.0038 (0.0084)
Age 12 Dummy	-0.0207 (0.0153)	Father's educ. - 3	-0.0047 (0.0074)
Age 13 Dummy	**-0.0304** (0.0145)	Father's educ. - 4	-0.0011 (0.0102)
Age 14 Dummy	0.0052 (0.0176)	Constant	0.0061 (0.0315)
R^2	0.0904	No. observations	19,143

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.32: Model 2 for Emotional, Psych. or Nervous Difficulties - de Oliveira

Chronic condition available for children 6-15 only.

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0118** (0.0054)	White	0.0063 (0.0070)
Emo., Psych. or Nerv. Diff.	**0.2262** (0.0299)	Log of family size	-0.0002 (0.0131)
Emo., Psych. or Nerv. Diff.*Ln income	0.0194 (0.0553)	Male	0.0031 (0.0054)
		PMK female	0.0067 (0.0103)
		Mother's age at child birth	0.0002 (0.0006)
		PMK depression score	**0.0028** (0.0006)
		Mother - poor health	**0.1377** (0.0074)
		Father - poor health	**0.0945** (0.0068)
Age 6 Dummy	0.0034 (0.0145)	Mother - smoking	0.0127 (0.0068)
Age 7 Dummy	-0.0006 (0.0148)	Father - smoking	-0.0042 (0.0063)
Age 8 Dummy	-0.0027 (0.0147)	Mother's educ. - 2	-0.0151 (0.0092)
Age 9 Dummy	-0.0036 (0.0148)	Mother's educ. - 3	**-0.0203** (0.0085)
Age 10 Dummy	-0.0152 (0.0146)	Mother's educ. - 4	**-0.0384** (0.0113)
Age 11 Dummy	-0.0147 (0.0138)	Father's educ. - 2	-0.0049 (0.0084)
Age 12 Dummy	-0.0226 (0.0152)	Father's educ. - 3	-0.0049 (0.0074)
Age 13 Dummy	**-0.0285** (0.0144)	Father's educ. - 4	-0.0020 (0.0102)
Age 14 Dummy	0.0060 (0.0175)	Constant	0.0597 (0.0315)
R^2	0.0892	No. observations	19,143

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.33: Model 2 for Any Other Long-term Condition - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0105** (0.0040)	White	0.0046 (0.0053)
Any other long-term condition	**0.2193** (0.0144)	Log of family size	0.0156 (0.0097)
Any other long-term condition*Ln income	0.0019 (0.0254)	Male	**0.0114** (0.0040)
Age 1 Dummy	**0.0379** (0.0108)	PMK female	0.0088 (0.0073)
Age 2 Dummy	0.0113 (0.0087)	Mother's age at child birth	0.0002 (0.0005)
Age 3 Dummy	**0.0262** (0.0095)	PMK depression score	**0.0025** (0.0005)
Age 4 Dummy	**0.0263** (0.0086)	Mother - poor health	**0.1310** (0.0056)
Age 5 Dummy	**0.0308** (0.0093)	Father - poor health	**0.0909** (0.0053)
Age 6 Dummy	**0.0342** (0.0094)	Mother - smoking	**0.0132** (0.0051)
Age 7 Dummy	**0.0311** (0.0098)	Father - smoking	-0.0043 (0.0047)
Age 8 Dummy	**0.0335** (0.0097)	Mother's educ. - 2	**-0.0207** (0.0073)
Age 9 Dummy	**0.0300** (0.0099)	Mother's educ. - 3	**-0.0237** (0.0067)
Age 10 Dummy	**0.0190** (0.0096)	Mother's educ. - 4	**-0.0335** (0.0086)
Age 11 Dummy	**0.0201** (0.0099)	Father's educ. - 2	-0.0069 (0.0065)
Age 12 Dummy	0.0152 (0.0106)	Father's educ. - 3	-0.0094 (0.0057)
Age 13 Dummy	0.0036 (0.0109)	Father's educ. - 4	-0.0070 (0.0075)
Age 14 Dummy	**0.0423** (0.0137)	Constant	-0.0003 (0.0216)
Age 15 Dummy	**0.0355** (0.0152)		
R^2	0.0826	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.34: Model 2 for Any Chronic Condition - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	-0.0043 (0.0038)	White	0.0027 (0.0050)
Any Chronic Condition	**0.1306** (0.0041)	Log of family size	**0.0372** (0.0093)
Any Chronic Condition*Ln income	**-0.0178** (0.0068)	Male	0.0024 (0.0038)
Age 1 Dummy	**0.0237** (0.0105)	PMK female	0.0037 (0.0071)
Age 2 Dummy	-0.0063) (0.0084)	Mother's age at child birth	0.0005 (0.0005)
Age 3 Dummy	0.0064 (0.0092)	PMK depression score	**0.0020** (0.0004)
Age 4 Dummy	-0.0017 (0.0084)	Mother - poor health	**0.1199** (0.0054)
Age 5 Dummy	-0.0019 (0.0090)	Father - poor health	**0.0901** (0.0051)
Age 6 Dummy	-0.0013 (0.0091)	Mother - smoking	**0.0128** (0.0048)
Age 7 Dummy	-0.0055 (0.0096)	Father - smoking	-0.0070 (0.0045)
Age 8 Dummy	-0.0073 (0.0094)	Mother's educ. - 2	**-0.0148** (0.0068)
Age 9 Dummy	-0.0116 (0.0097)	Mother's educ. - 3	**-0.0229** (0.0064)
Age 10 Dummy	**-0.0277** (0.0093)	Mother's educ. - 4	**-0.0346** (0.0081)
Age 11 Dummy	**-0.0223** (0.0097)	Father's educ. - 2	-0.0058 (0.0061)
Age 12 Dummy	**-0.0310** (0.0103)	Father's educ. - 3	-0.0098 (0.0053)
Age 13 Dummy	**-0.0397** (0.0107)	Father's educ. - 4	-0.0054 (0.0070)
Age 14 Dummy	-0.0039 (0.0136)	Constant	-0.0316 (0.0206)
Age 15 Dummy	-0.0068 (0.0149)		
R^2	0.1139	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.35: Model 2 for Activity Limitations - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0101** (0.0039)	White	0.0053 (0.0052)
Activity Limitations	**0.3326** (0.0161)	Log of family size	0.0163 (0.0107)
Activity Limitations*Ln income	-0.0349 (0.0254)	Male	**0.0113** (0.0039)
Age 1 Dummy	**0.0358** (0.0107)	PMK female	0.0075 (0.0072)
Age 2 Dummy	0.0104) (0.0086)	Mother's age at child birth	0.0001 (0.0005)
Age 3 Dummy	**0.0264** (0.0094)	PMK depression score	**0.0020** (0.0005)
Age 4 Dummy	**0.0239** (0.0085)	Mother - poor health	**0.1269** (0.0056)
Age 5 Dummy	**0.0275** (0.0092)	Father - poor health	**0.0895** (0.0052)
Age 6 Dummy	**0.0310** (0.0093)	Mother - smoking	0.0119 (0.0050)
Age 7 Dummy	**0.0300** (0.0097)	Father - smoking	-0.0048 (0.0046)
Age 8 Dummy	**0.0276** (0.0096)	Mother's educ. - 2	**-0.0202** (0.0071)
Age 9 Dummy	**0.0253** (0.0098)	Mother's educ. - 3	**-0.0237** (0.0066)
Age 10 Dummy	0.0118 (0.0095)	Mother's educ. - 4	**-0.0343** (0.0084)
Age 11 Dummy	0.0128 (0.0099)	Father's educ. - 2	-0.0078 (0.0063)
Age 12 Dummy	0.0050 (0.0105)	Father's educ. - 3	-0.0085 (0.0055)
Age 13 Dummy	-0.0015 (0.0108)	Father's educ. - 4	-0.0057 (0.0073)
Age 14 Dummy	0.0243 (0.0137)	Constant	0.0054 (0.0212)
Age 15 Dummy	0.0223 (0.0149)		
R^2	0.1131	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.36: Model 2 for Any Chronic Cond. and/or Act. Limit. - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	-0.0021 (0.0038)	White	0.0043 (0.0051)
Any Chronic Cond. and/or Act. Limit.	**0.1662** (0.0056)	Log of family size	0.0337 (0.0095)
Any Chronic Cond. and/or Act. Limit.*Ln income	**-0.0304** (0.0093)	Male	0.0047 (0.0039)
Age 1 Dummy	**0.0246** (0.0105)	PMK female	0.0064 (0.0072)
Age 2 Dummy	-0.0051) (0.0085)	Mother's age at child birth	0.0004 (0.0005)
Age 3 Dummy	0.0094 (0.0092)	PMK depression score	**0.0021** (0.0005)
Age 4 Dummy	0.0011 (0.0084)	Mother - poor health	**0.1231** (0.0055)
Age 5 Dummy	0.0025 (0.0090)	Father - poor health	**0.0911** (0.0052)
Age 6 Dummy	0.0012 (0.0092)	Mother - smoking	**0.0131** (0.0049)
Age 7 Dummy	-0.0018 (0.0096)	Father - smoking	-0.0069 (0.0046)
Age 8 Dummy	-0.0023 (0.0095)	Mother's educ. - 2	-0.166 (0.0070)
Age 9 Dummy	-0.0082 (0.0098)	Mother's educ. - 3	**-0.0242** (0.0065)
Age 10 Dummy	**-0.0213** (0.0094)	Mother's educ. - 4	**-0.0350** (0.0083)
Age 11 Dummy	-0.0179 (0.0097)	Father's educ. - 2	-0.0052 (0.0062)
Age 12 Dummy	**-0.0255** (0.0104)	Father's educ. - 3	-0.0097 (0.0054)
Age 13 Dummy	**-0.0352** (0.0107)	Father's educ. - 4	-0.0049 (0.0072)
Age 14 Dummy	0.0011 (0.0136)	Constant	-0.0330 (0.0211)
Age 15 Dummy	-0.0049 (0.0149)		
R^2	0.1276	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.37: Model 2 for Heart and/or Kidney Cond. or Disease - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0114** (0.0041)	White	0.0030 (0.0053)
Heart and/or Kidney Cond. or Disease	**0.1986** (0.0245)	Log of family size	0.0143 (0.0097)
Heart and/or Kidney Cond. or Disease*Ln income	0.0211 (0.0408)	Male	**0.0129** (0.0041)
Age 1 Dummy	**0.0400** (0.0109)	PMK female	0.0096 (0.0074)
Age 2 Dummy	0.0130) (0.0087)	Mother's age at child birth	0.0000 (0.0005)
Age 3 Dummy	**0.0278** (0.0095)	PMK depression score	**0.0027** (0.0005)
Age 4 Dummy	**0.0274** (0.0086)	Mother - poor health	**0.1317** (0.0057)
Age 5 Dummy	**0.0331** (0.0093)	Father - poor health	**0.0921** (0.0053)
Age 6 Dummy	**0.0385** (0.0095)	Mother - smoking	**0.0139** (0.0051)
Age 7 Dummy	**0.0370** (0.0099)	Father - smoking	-0.0051 (0.0048)
Age 8 Dummy	**0.0370** (0.0097)	Mother's educ. - 2	**-0.0215** (0.0073)
Age 9 Dummy	**0.0349** (0.0099)	Mother's educ. - 3	**-0.0233** (0.0068)
Age 10 Dummy	**0.0234** (0.0096)	Mother's educ. - 4	**-0.0330** (0.0087)
Age 11 Dummy	**0.0246** (0.0100)	Father's educ. - 2	-0.0063 (0.0066)
Age 12 Dummy	0.0188 (0.0106)	Father's educ. - 3	-0.0076 (0.0058)
Age 13 Dummy	0.0094 (0.0110)	Father's educ. - 4	-0.0045 (0.0075)
Age 14 Dummy	**0.0462** (0.0138)	Constant	0.0046 (0.0218)
Age 15 Dummy	**0.0376** (0.0152)		
R^2	0.0845	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.38: Model 2 for Learn. Disab. and/or Emo., Psych. or Nerv. Diff. - de Oliveira

Chronic condition available for children 6-15 only.

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0114** (0.0054)	White	0.0058 (0.0070)
Learn. Disab. and/or Emo., Psych. or Nerv. Diff.	**0.1619** (0.0188)	Log of family size	-0.0004 (0.0131)
Learn. Disab. and/or Emo., Psych. or Nerv. Diff.*Ln income	-0.0141 (0.0307)	Male	0.0004 (0.0054)
		PMK female	0.0054 (0.0102)
		Mother's age at child birth	0.0001 (0.0006)
		PMK depression score	**0.0026** (0.0006)
		Mother - poor health	**0.1374** (0.0074)
		Father - poor health	**0.0941** (0.0067)
Age 6 Dummy	0.0051 (0.01146)	Mother - smoking	0.0117 (0.0068)
Age 7 Dummy	0.0033 (0.0149)	Father - smoking	-0.0039 (0.0063)
Age 8 Dummy	0.0015 (0.0147)	Mother's educ. - 2	-0.0143 (0.0092)
Age 9 Dummy	-0.0005 (0.0149)	Mother's educ. - 3	**-0.0194** (0.0085)
Age 10 Dummy	-0.0130 (0.0147)	Mother's educ. - 4	**-0.0378** (0.0113)
Age 11 Dummy	-0.0122 (0.0139)	Father's educ. - 2	-0.0040 (0.0083)
Age 12 Dummy	-0.0212 (0.0153)	Father's educ. - 3	-0.0049 (0.0074)
Age 13 Dummy	-0.0300 (0.0145)	Father's educ. - 4	-0.0042 (0.0102)
Age 14 Dummy	0.0054 (0.0176)	Constant	0.0587 (0.0314)
R^2	0.0922	No. observations	19,143

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Table 3.39: Model 2 for Other Chronic Conditions (combined) - de Oliveira

Variable	Coefficient	Variable	Coefficient
Ln income	**-0.0101** (0.0040)	White	0.0042 (0.0052)
Other Chronic Conditions (combined)	**0.2311** (0.0138)	Log of family size	0.0164 (0.0097)
Other Chronic Conditions (combined)*Ln income	-0.0050 (0.0254)	Male	**0.0109** (0.0040)
Age 1 Dummy	**0.0374** (0.0108)	PMK female	0.0081 (0.0072)
Age 2 Dummy	0.0107) (0.0087)	Mother's age at child birth	0.0001 (0.0005)
Age 3 Dummy	**0.0257** (0.0094)	PMK depression score	**0.0025** (0.0005)
Age 4 Dummy	**0.0253** (0.0086)	Mother - poor health	**0.1308** (0.0056)
Age 5 Dummy	**0.0300** (0.0092)	Father - poor health	**0.0904** (0.0053)
Age 6 Dummy	**0.0332** (0.0094)	Mother - smoking	**0.0131** (0.0051)
Age 7 Dummy	**0.0299** (0.0098)	Father - smoking	-0.0046 (0.0047)
Age 8 Dummy	**0.0324** (0.0097)	Mother's educ. - 2	**-0.0200** (0.0072)
Age 9 Dummy	**0.0289** (0.0099)	Mother's educ. - 3	**-0.0235** (0.0067)
Age 10 Dummy	0.0180 (0.0096)	Mother's educ. - 4	**-0.0331** (0.0086)
Age 11 Dummy	0.0187 (0.0099)	Father's educ. - 2	-0.0078 (0.0065)
Age 12 Dummy	**0.0137** (0.0105)	Father's educ. - 3	-0.0097 (0.0057)
Age 13 Dummy	0.0020 (0.0108)	Father's educ. - 4	-0.0073 (0.0074)
Age 14 Dummy	**0.0401** (0.0136)	Constant	0.0008 (0.0215)
Age 15 Dummy	**0.0341** (0.0151)		
R^2	0.0990	No. observations	33,025

Observations were clustered by child ID. Standard errors are shown in brackets.

Coefficients in bold are statistically significant at the 5% level.

Conclusion

It has been established that the well-known positive association between health and income in adulthood has antecedents in childhood. Case et al.'s (2002) paper was the first to examine the relationship between child health and household income, and provided the impetus for others to investigate this relationship further using data from other countries.

We contribute to the literature in several ways. First, we propose an alternative model specification to investigate the income-health gradient in childhood. We seek to understand whether this relationship holds for Canadian children, how it behaves with child age and the potential underlying mechanisms. Our proposed framework, which we denominate the *de Oliveira* model provides evidence that the gradient in Canada is not as strong as suggested by Currie and Stabile (2003) and, furthermore, that it does not increase as children age. With regards to the underlying mechanisms, we find that some of the differences between high- and low-income children are due to the latter being exposed to more bad health shocks. Moreover, we provide new evidence that parents' health status plays an important and independent role in explaining children's health status, particularly maternal health.

Second, we employ nonparametric models to assess whether this type of methodology can provide additional insight in understanding the income-health gradient in childhood. To our knowledge, no other study has specifically examined this topic using nonparametric techniques. We find that our nonparametric model provides a 33% and 31% improvement in terms of the model's predictive power in- and out-of sample, respectively, when compared to its parametric counterpart, suggesting that our nonparametric model is closer to the true data generating process than our parametric model. Moreover, our estimates indicate that the probability of a child being in excellent health varies with income but, contrary to earlier work, the gradient does not increase with age. We also confirm the importance of parents' health, especially that of the mother, in explaining child health. However, contrary to our previous findings, we find that the exclusion of parental health status in our model framework does not change how the income gradient in child health behaves with age – even when we exclude parental health from the model, the income-health gradient remains constant with age. In sum, our results indicate that a child's initial health endowment and household income are strong predictors of their subsequent health status.

Third, and finally, we provide insight on the impact of chronic conditions on Canadian children's health status and how the former impact the latter by income levels. Generally, our results suggest that income does not have a significant impact on the management of child chronic conditions, contrary to Case et al.'s (2002) findings. Furthermore, we do not find that the impact of chronic conditions on the probability of being in poor health varies by income, with the exception of asthma and mental handicap. Thus, our findings do not support the hypothesis that income protects children from the adverse effect of chronic conditions. In addition, we do not find any evidence that the income effect increases with age. This is contrary to the results found for American children. Thus, our research suggest that income-related policies may have little or no impact in improving child health.

References

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