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Understanding Child Health Inequities using Distributional Decomposition

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Abbreviations:

BMI: Body mass index
SDQ: Strengths and Difficulties Questionnaire
ITC: Infant-toddler checklist

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Anne E Fuller conceptualized and designed the study, conducted the initial analyses, and drafted the initial manuscript, and reviewed and revised the final manuscript.
Arjumand Siddiqi conceptualized and designed the study, reviewed the analyses, and reviewed and revised the final manuscript.
Faraz V Shahidi and Vincent Hildebrand assisted with analysis, reviewed analyses, and reviewed and revised the final manuscript.
Laura N Anderson conceptualized and designed the study and reviewed and revised the final manuscript.
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Jonathon L Maguire conceptualized and designed the study and reviewed and revised the final manuscript.
Catherine S Birken conceptualized and designed the study, reviewed analyses, and reviewed and revised initial manuscript drafts and the final manuscript.
All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

ABSTRACT

Objectives: Children from low-income households are at an increased risk of social, behavioral, and physical health problems. Prior studies have generally relied on dichotomous outcome measures. However, inequities may exist along the range of outcome distribution. Our objective was to examine differences in distribution of three child health outcomes by income: body mass index (BMI), behavior difficulties, and development.

Methods: This was a cross-sectional study of children enrolled in a practice-based research network. The independent variable was annual household income, dichotomized at the median income for Toronto (< $80,000 or ≥$80,000 CAD). Dependent variables were: 1) growth (BMI z-score (zBMI) at 5 years); 2) behavior (Strengths and Difficulties Questionnaire (SDQ) at 3-5 years); 3) development (Infant Toddler Checklist (ITC) at 18 months). We used distributional decomposition to compare distributions of these outcomes for each income group, and then to construct a counterfactual distribution that describes the hypothetical distribution of the low-income group with the predictor profile of the higher-income group.

Results: We included data from 1628 (zBMI), 649 (SDQ) and 1405 (ITC) children. Children with lower family income had a higher risk distribution for all outcomes. For all outcomes, the counterfactual distribution, representing the distribution of children with lower-income with the predictor profile of the higher income group, was more favorable than their observed distributions.

Conclusion: Interventions to reduce income inequities in child health by addressing common predictors may yield improvements for those in the low-risk range of outcome distributions; targeted interventions are likely needed for those at high risk.

Strengths and limitations of this study

Strengths of this study include:

- large sample of young children in a major urban area in Canada
- Use of employs a novel and revealing analysis for this population and these outcomes
- All outcomes defined using objective measures and validated instruments relevant to clinical practice

Limitations of this study include:

- Lower proportion of children from lower-income compared to higher-income households
- Limits to generalizability related to recruitment from primary care practices in an urban setting

INTRODUCTION

Income is an important determinant of child health, with children living in households from the lowest income quintile experiencing poorer health outcomes on multiple measures.[1] Lower socioeconomic status, the broader construct that speaks to the material and social resources of families that are linked to income and education, has been associated with poorer child health outcomes across domains[2], including increased risk learning disability or serious behavioral difficulty, poorer educational outcomes[3], and mental health challenges.[4]

There is a strong argument in favour of using continuous outcome measures in population health research. While population-level means or categorical definitions of outcomes may show improvement in important health outcomes over time, inequities may be overlooked by not examining the distributions of outcomes.[5] Research findings based on categorized outcomes may be easier to use in clinical practice. However, studying continuous measures can reduce bias that may be introduced with assigning categories and may increase statistical power.[6] Understanding inequities in the full range of outcome distribution may also provide more nuanced findings to inform specific interventions.[7,8]

Obesity, mental illness and developmental delays are among the most significant chronic conditions faced by children and they share risk and protective factors,[9,10] including poverty and childhood adversity.[11] However, there is limited research examining income inequities in very young children, and data from population-based clinical cohorts is scarce. Our first objective was to examine differences in the distribution of three child health outcomes in young children by income: body mass index (BMI), behavior difficulties, and development. Our second objective

was to explore the extent to which differences across the income distribution can be accounted for by common predictors for each outcome.

METHODS

Study Design, Setting and Participants

This was a cross-sectional study of children enrolled in the TARGet Kids! Research Study. TARGet Kids! is a primary care practice-based research network in the Greater Toronto Area and Kingston, Ontario, and Montreal, Quebec. Children less than 6 years old are recruited by trained research personnel embedded at primary care paediatric and family medicine practices. They are followed prospectively into adolescence. Participants complete standardized questionnaires and have anthropometrics measured at scheduled healthcare maintenance visits and are followed yearly. This cohort includes outcomes collected from 2008-2019. The study protocol and sample population have been described in detail.[12]

Exclusion criteria at enrollment are health conditions affecting growth, severe developmental delay, chronic health conditions (except asthma and high functioning autism), birth less than 32 weeks' gestation and families unable to complete questionnaires in English. This study was approved by the Research Ethics Board at the Hospital for Sick Children, Unity Health Toronto, and McGill University.

Patient and Public Involvement

The TARGet Kids! Research Network includes a Parent and Clinician Team (PACT) which is actively involved in guiding the research directions and priorities of TARGet Kids!.[13] As this study was a secondary analysis of existing TARGet Kids! data, parents and patients were not actively involved in the design. Results are disseminated to study participants through study communications and the TARGet Kids! website.

Study Assessments

Independent Variable

The independent variable was parent-reported annual household income. It is collected in the standardized TARGet Kids nutrition and health questionnaire with a single question, "what was your family income before taxes last year," with 13 response categories, ranging from "less than $10,000" to "greater than $500,000." We created two categories, dichotomized at approximately the median household income in the Toronto Census Metropolitan Area based on the 2016 Canadian census (< $80,000 or ≥$80,000 CAD).We dichotomized at the median income.[14] We selected this cut point to represent a common measure of household income, and to ensure a robust sample size in both groups to permit the analysis.

Dependent Variables

Dependent variables were: 1) growth (body mass index z-score (zBMI) at 5 years); 2) child behavior (total difficulties score on the Strengths and Difficulties Questionnaire (SDQ) at 3-5 years); 3) development (total score on the Infant Toddler Checklist (ITC) at 18 months).

To assess zBMI, height and weight were measured by trained research assistants according to standard protocols.[15] BMI was calculated as weight in kilograms divided by squared heighted in meters and measured at 5 years old. Age and sex standardized zBMI was calculated using the recommended WHO growth standards.[16]

To assess child behavior, we used the Strengths and Difficulties Questionnaire (SDQ) total difficulties score, measured between 3 and 5 years of age. The SDQ has been validated in children of all ages and across multiple countries and cultural groups.[17,18] The score is comprised of 20 questions, and measures emotional problems, conduct problems, hyperactivity, and peer problems. Higher score indicates greater difficulties.

To assess child development, we used the Infant Toddler Checklist (ITC – also known as the Communication and Symbolic Behavior Scales: Developmental Profile), measured between 18 and 24 months.[19,20] This is a measure for clinical screening of social and communication developmental risk, validated for use between 6 and 24 months. Lower score indicates greater developmental risk.

Covariates

Child and maternal characteristics were used to produce predictor profiles. For children, these were age (months), sex, birthweight (kilograms), and living arrangement (living with both parents, or any other arrangement) for all models; gestational age (32 to 36 weeks, 37 weeks and greater) was included for ITC models only as an important predictor of development.[21], and total months breastfed. For mothers, these were maternal age (years), education (high school or less, university or more), immigration status (born in Canada, born outside of Canada), ethnic ancestry (European/White, other) and body mass index (kg/m^2). Breastfeeding duration, and maternal BMI were included in the BMI models only as important predictors of child BMI.[22]

Statistical Analysis

We used descriptive statistics to characterize the study population and describe the means and proportions of the outcomes of interest. We used Mann-Whitney and chi-square tests to compare predictors by income category. Using methods described by Siddiqi et al[7], who adapted the DiNardo-Fortin-Lemieux decomposition[23], we then measured the *distributional inequality*. We first estimated the probability densities of each outcome for each income subgroup using an adaptative kernel estimator. We then calculated d*istributional inequality* as the difference between the kernel density estimates of the two income subgroups. At any given point, it measures the difference between proportion of children in the lower-income group and those in

the higher income group. We depicted the kernel density distributions and the distributional inequality graphically.

We then proceeded with *distributional decomposition* separately for each outcome. Distributional decomposition offers a method to identify the proportion of inequality at each point in the outcome distribution that can be explained by a set of common predictors using a simple reweighting method originally developed by DiNardo et al.[23] We estimated the counterfactual density function for each outcome of the lower-income group that would prevail were children in the lower-income group given the predictors of the higher income group. This involves reweighting the density function of the lower-income group such that the reweighted sample of children in the lower-income group has the same predictors of the children in the higher income group.[7,23] We then used the counterfactual weight to reweight the kernel density estimates to produce the counterfactual distribution. This counterfactual density distribution demonstrates how the observed distribution of the children in the lower-income group would change if they took on the predictor profile of children in the higher-income group. We plotted this re-weighted counterfactual distribution to compare it visually to the original distributions for the higher- and lower-income groups.

Because of smaller numbers of children at the high and low ends of the distributions of each variable for the lower-income group, we undertook a sensitivity analysis, reversing the re-weighting by applying the predictor profile of the lower-income group to the higher-income group. This increases the likelihood of achieving "common support", where all configurations of predictor profiles of the re-weighted group are present in the reference group. We would expect the distribution to appear like the inverse of the first one. Statistical analyses were performed using Stata (v 14.2, College Station, Texas).[24]

RESULTS

For the BMI outcome 2,123 children between 60 and 71 months had complete outcome and income reported, of whom 1,628 had complete information for all variables and were included. For our SDQ cohort, 774 had complete outcome and income reported, 649 of whom had complete information for each variable and were included. For our ITC cohort, 1698 had complete outcome and income reported, 1405 of whom had complete information for each variable and were included (Figure 1).

The predictor profiles of children from higher and lower-income households are shown in Table 1. Children from lower-income households had a shorter duration of breastfeeding, had mothers who were younger; a lower proportion lived with both parents, had fewer mothers with a university education; a greater proportion had mothers who were immigrants to Canada or reported ethnic ancestry as other than European.

Body Mass Index

A greater proportion of children with higher income were in the normal weight category compared with children with lower-income (84.9% vs 77.4%), while a greater proportion of children with low income were in the underweight, overweight, and obesity categories (Table 1). Comparing the density distributions by income category, the distribution of children with high income was more concentrated around a zBMI of zero, while a higher proportion of children with low-income were at the tails of the distribution (Figure 2a). Figure 2b shows the difference between the observed distributions.

When children from lower-income households were re-weighted to have the predictor profiles of children from higher-income households, the distribution of zBMI within the normal range (-1 to 1) narrowed. This re-weighted distribution is shown with the observed distributions

in Figure 2c. The residual, unexplained difference between the re-weighted distribution and the higher-income distribution is shown in Figure 2d. In this normal range, the difference between the re-weighted distribution for children from lower-income households and the distribution of children from higher-income households decreased substantially (Figure 2d). However, at the tails of the distribution, the re-weighted distribution curve was largely unchanged from the observed distribution.

Strengths and Difficulties Questionnaire

Children from higher-income households had a lower mean SDQ score (7.2 vs 9.0) (table 1). Comparing the density distributions by income category, the differences in distribution were most notable in the lower and middle range of the score distribution, which had a lower proportion of children from lower-income households (Figure 3a). There was a greater proportion of children from lower-income households in the high- risk range (>17) as well. Figure 3b shows the difference between the observed distributions.

The re-weighted distribution of SDQ total difficulties score for children from lower-income families in the low-risk range shifted to the left, with a greater proportion having even *lower scores* than before. This re-weighted distribution is shown with the observed distributions in Figure 3c. The residual distribution had two peaks in the low-risk range, which were higher than the observed distribution for children from higher-income households, and a third peak in the high-risk range. The residual, unexplained difference between the re-weighted distribution and the high-income distribution is shown in Figure 3d.

Infant-Toddler Checklist

Children from higher-income households had a higher mean ITC score indicating lower risk (46.6 vs 44.5) (table 1). Comparing density distribution by income, the differences were

notable across the distribution, with a greater proportion of children from lower-income households in the higher risk range (Figure 4a). Figure 4b shows the difference between the observed distributions.

The re-weighted distribution of ITC score for children from lower-income households shows that the distribution in the low-risk range (higher scores) is like the observed distribution from high income households, indicating that common predictors explain much of the difference. This re-weighted distribution is shown with the observed distributions in Figure 4c. However, as total ITC score decreases into higher risk ranges, the re-weighted distribution still shows a greater proportion of children from low-income households with lower scores. The residual, unexplained difference between the re-weighted distribution and the high-income distribution is shown in Figure 4d.

Sensitivity Analyses

Our sensitivity analysis, presented in appendix 2, which re-weighted the predictor profiles of children from higher-income households to have the predictor profile of children from lower-income households, showed a generally similar pattern in the low-risk range of the distribution for each outcome. Most notably, for SDQ, this analysis resolves the second peak of unexplained difference in the high-risk range, suggesting this may be due to low sample size in the lower-income group at the high end of the distribution.

DISCUSSION

In this study with a large cohort of young children, we found that there were notable differences between the distributions of children from higher and lower-income households for three important outcomes studied: zBMI, total behavioral difficulties, and developmental risk, with a greater proportion of children with higher-income in the low-risk range of the distribution,

and a greater proportion of those with lower-income in the higher risk range. When the distributions for children with lower-income were re-weighted to give them the predictor profiles of children with higher-income children, children with lower-income already in the low-risk range adopted a distribution that appeared to be *even lower risk.* After re-weighting, children in the lower-income group with behavioral and developmental outcomes in the high-risk range adopted a distribution with a lower proportion of children at high risk. This was not the case for zBMI, where the re-weighted distributions were like the observed distributions. Comparing observed distributions, the difference between income categories in the higher risk ranges (obesity, underweight) are smaller than the differences in the lower risk range (normal weight).

By comparing the observed distributions of continuous measures of child health by income, we can appreciate inequalities that may not be captured using categorical definitions that are used for clinical risk stratification. Categorical measurement can collapse variation within each category, and this variation can yield important information. These inequalities may have clinical meaning; for example, small differences in SDQ score or in zBMI are related to differences in long-term behavior and cardiometabolic outcomes, respectively.[25,26] Small differences in risk early in life may continue to grow through the life-course. For example, higher BMI in early life is associated with greater risk of obesity later.[27] Comparing distributions offers the opportunity to disaggregate differences that may not be appreciated with categorical outcome definitions.

The distributional decomposition analysis adds a further layer to our understanding of potential explanations for these inequities. For all outcomes, we found that the inequality between the observed distribution of children with higher-income and the counterfactual distribution was lower than the inequality between observed distributions of children within the

"low-risk" range of the distribution. However, in the higher risk range, the counterfactual reduced the inequality to a variable degree depending on outcome. We suspect that the determinants of having clinically meaningful concerns about growth, behavior or development are different than the determinants of where an individual falls in the lower risk range. For example, clinically significant behavior difficulties on the SDQ may represent an underlying behavior disorder such as attention-deficit disorder, while within the low-risk range, other factors such as parenting behaviors, which are more closely related to predictors in our predictor profiles, may be more influential.

For zBMI, the counterfactual distribution demonstrates that routine predictors of BMI explain some of the income-related inequality in the distribution within the normal range but does not explain the inequalities observed for children with obesity and underweight. It is possible that the determinants of obesity could be different than the determinants of underweight[28], or that low income is a primary driver of BMI.[29,30]

Compared to zBMI, routine predictors of child behavior and mental health can explain more of the income-related inequality in the distribution of SDQ score, including at the higher range of the distribution. The highest risk range of the distribution may have represented children with significant morbidity, which likely has different predictors than a lower score. Our sensitivity analysis, which re-weighted the children with high-income to have predictors of children with low-income, resolved this issue, suggesting sample size in the distribution of predictors for the lower-income group may be a contributor. The counterfactual distribution of the ITC was the closest to the observed distribution of children with higher-income of the three child health outcomes studied. It is possible that ITC had the strongest income-related predictors

of the outcome included in the model, with parental education as a particularly important driver of parent-toddler communication, promoting language development.[31]

This study has several strengths. It includes a large sample of young children in a major urban area in Canada and employs a novel and revealing analysis. All outcomes were defined using objective measures (zBMI) and validated instruments (SDQ and ITC), which are relevant to clinical practice. This study also has certain limitations. Our sample had a lower proportion of children in the lower-income group, and particularly at the tail ends of distributions where there were fewer children overall, fewer children with each covariate pattern may have led to reduced robustness of the re-weighted counterfactual. Future research could explore alterative categories of income. There was a smaller proportion of participants with certain characteristics which required categorization of certain predictors and did not allow for stratification by potentially important predictors (eg. race/ethnicity). Children with missing data may come from households with low-income or other stressors and are not represented. Additionally, it is likely that there are other meaningful predictors of each outcome that were not included in our predictor profile. Finally, the study takes place in primary care practices in a major urban area in Canada, participating families had higher income, were English-speaking, and may not be representative of children who lack access to primary care, live in rural areas, or who have other barriers to participation in a longitudinal study. Future research should seek out populations of children who are under-represented in these analyses.

CONCLUSIONS

This study examining income-related differences in child growth, behavior, and development found that there were differences in the distribution of each outcome between children from higher and lower-income families, with children from lower-income families

showing a higher risk profile. Common predictors of each outcome partially explained the inequality, most notably in the low-risk range. These findings have important implications for health policies and interventions targeting income-based health inequities. Identifying that inequities likely have different predictors across the distribution suggests that interventions to reduce inequities by addressing common predictors may improve outcomes in the low-risk range. However, targeted interventions addressing income specifically, as well as the circumstances experienced by families with low-income, are likely needed for those at high risk.

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Table 1: Participant characteristics and outcomes by income category for each outcome cohort

Characteristic, n (%)	BMI[1] (n= 1,628)			SDQ[2] (n=649)			ITC[3] (n=1405)		
Predictors	Full Sample	Income ≥ $80000 (n=1180)	Income < $80000 (n=448)	Full Sample (649)	Income ≥ $80000 (n=539)	Income < $80000 (n=110)	Full Sample (n=1405)	Income ≥ $80000 (n=1106)	Income < $80000 (n=299)
Child									
Age (months) (mean, SD)	62.6 (2.8)	62.5 (2.7)	62.8 (3.0)	47.5 (12.3)	47.1 (12.3)	49.6 (12.2)	18.6 (0.98)	18.6 (0.97)	18.6 (1.0)
Sex									
Female	795 (48.8)	574 (48.6)	221 (49.3)	323 (49.7)	277 (51.4)	46 (41.8)	638 (45.3)	491 (48.5)	145 (48.5)
Male	833 (51.2)	606 (51.4)	227 (50.7)	326 (50.2)	262 (48.6)	64 (59.2)	614 (45.6)	615 (51.5)	154 (51.5)
Birthweight (kg) (mean, SD)	3.3 (0.6)	3.3 (0.6)	3.2 (0.7)	3.2 (0.6)	3.2 (0.6)	3.1 (0.6)	3.3 (0.7)	3.3 (0.7)	3.2 (0.7)
Gestational Age <37 weeks							189 (13.5)	147 (13.3)	42 (14.1)
Total Months Breastfed	12.6 (9.8)	12.9 (9.1)	12.0 (11.4)						
Lives with Both Parents	1497 (92.0)	1134 (96.1)	363 (81.0)	620 (95.5)	522 (96.8)	98 (88.7)	1346 (95.8)	1091 (97.7)	265 (88.3)
Parent									
Maternal Age at Birth (mean, SD)	33.3 (4.5)	33.9 (3.9)	31.6 (5.6)	33.6 (4.2)	34.0 (3.9)	31.7 (4.8)	33.9 (4.1)	34.4 (3.7)	32.2 (4.9)
Maternal Education									
University or more	1491 (91.6)	1138 (96.4)	353 (78.8)	534 (82.3)	476 (88.3)	58 (52.7)	1154 (82.1)	993 (99.8)	161 (53.9)
High school or less	137 (8.4)	42 (3.6)	95 (21.2)	115 (17.7)	63 (11.7)	52 (47.3)	251 (17.9)	113 (10.2)	138 (46.2)
Maternal BMI	24.7 (4.9)	24.3 (4.5)	25.7 (65.8)						
Mother Born in Canada									
Yes	1114 (68.4)	906 (76.8)	208 (46.4)	436 (67.2)	403 (74.8)	33 (30.0)	978 (69.6)	844 (76.3)	134 (44.8)
No	514 (31.6)	274 (23.2)	240 (453.6)	213 (32.8)	136 (25.2)	77 (70.0)	427 (30.4)	262 (23.7)	165 (55.2)
Maternal Ethnicity									
White/European	1162 (71.4)	909 (77.0)	253 (56.5)	390 (60.1)	353 (65.5)	37 (33.6)	886 (63.6)	766 (69.3)	120 (40.1)
Other	466 (28.6)	271 (23.0)	195 (43.5)	259 (39.9)	186 (34.5)	73 (66.4)	519 (36.9)	340 (30.7)	(59.9)
Outcomes									
BMI z-score Category (n, %)									
< -2.0 (underweight)	25 (1.2)	17 (1.1)	8 (1.3)						
≥-2.0 – <1.0 (normal)	1760 (82.3)	1276 (84.9)	471 (77.4)						
>1.0 – <2.0 (overweight)	273 (12.8)	175 (11.6)	96 (15.5)						
≥ 2.0 (obesity)	80 (3.7)	36 (2.4)	44 (7.1)						
SDQ Score (mean, SD)				7.5 (4.5)	7.2 (4.2)	9.0 (5.2)			
ITC Score (mean, SD)							46.6 (5.8)	47.4 (5.1)	44.5 (7.0)

[1] BMI: Body Mass Index; [2] SDQ: Strengths and Difficulties Questionnaire; [3] ITC: Infant Toddler Checklist

Figure 1: Defining the Cohorts

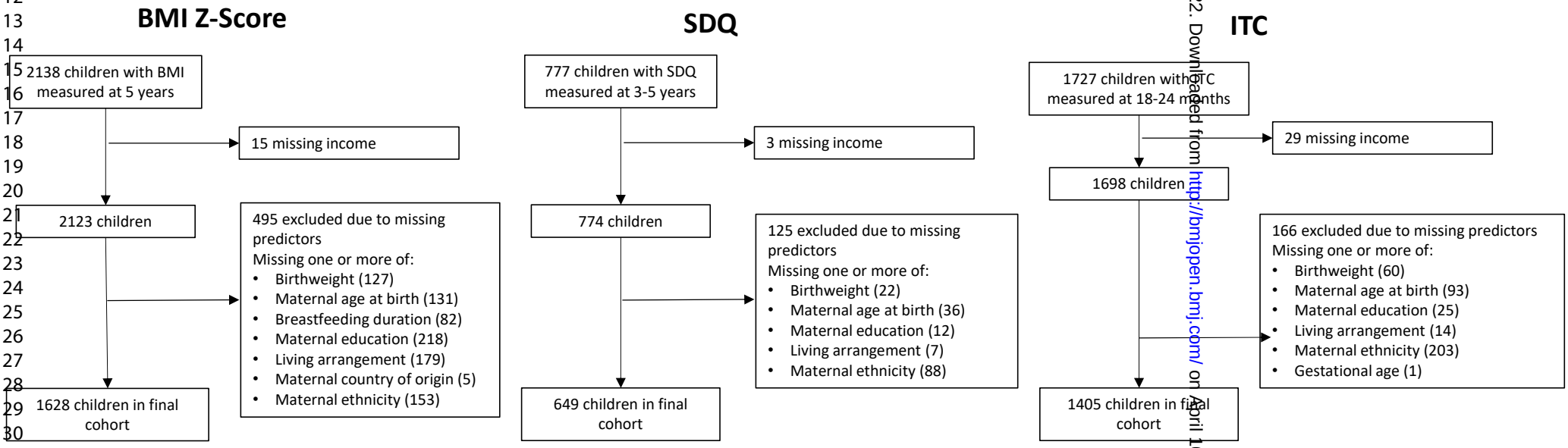
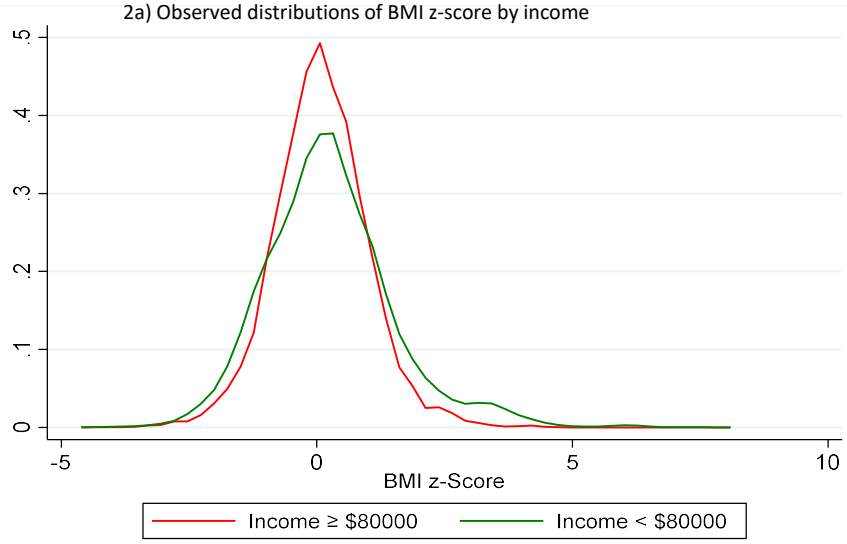
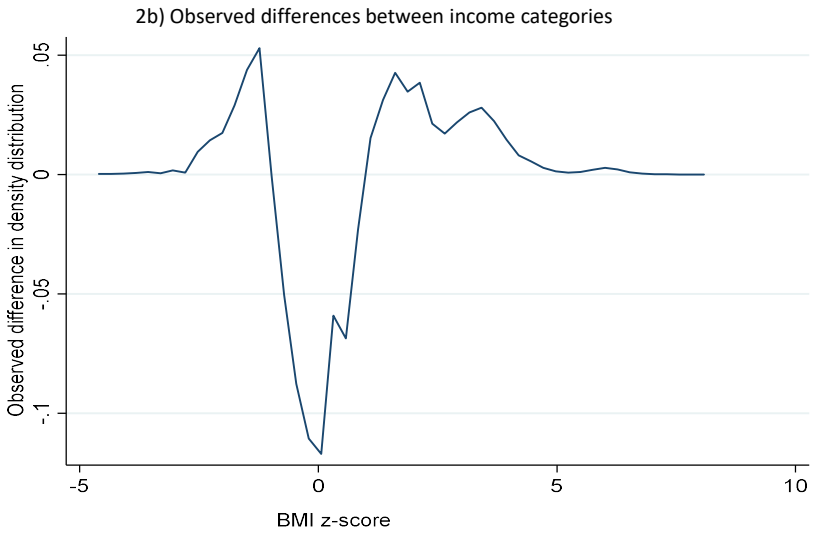
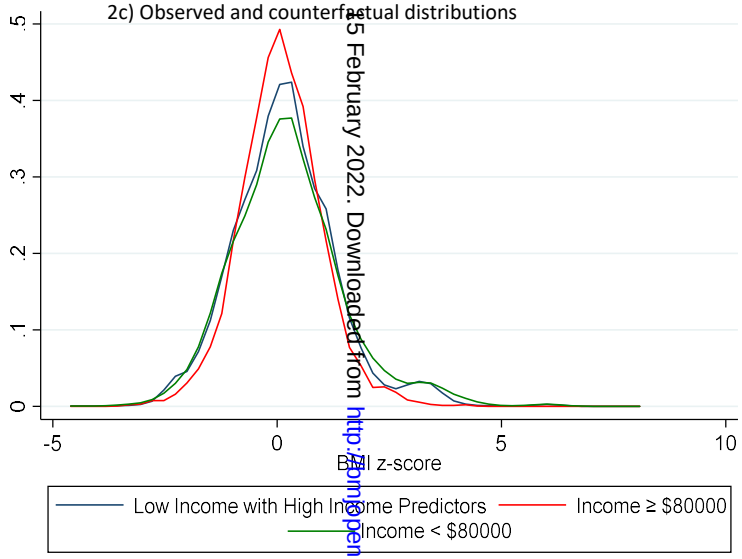


Figure 2: BMI z-score







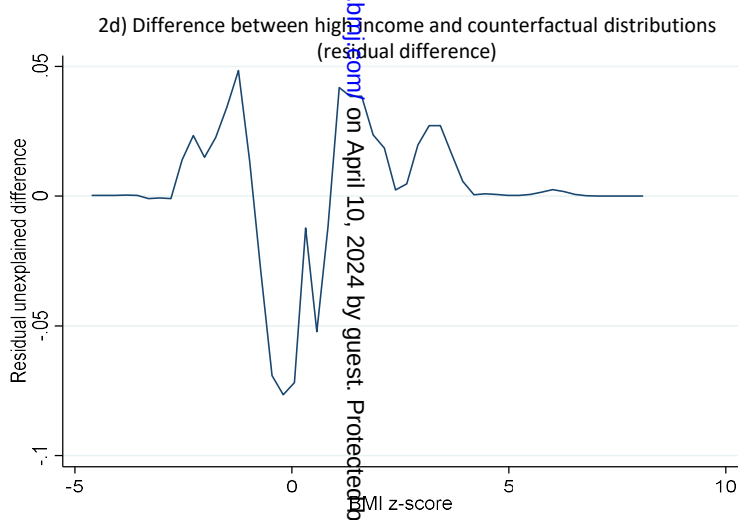


Figure 3: SDQ Total Difficulties Score

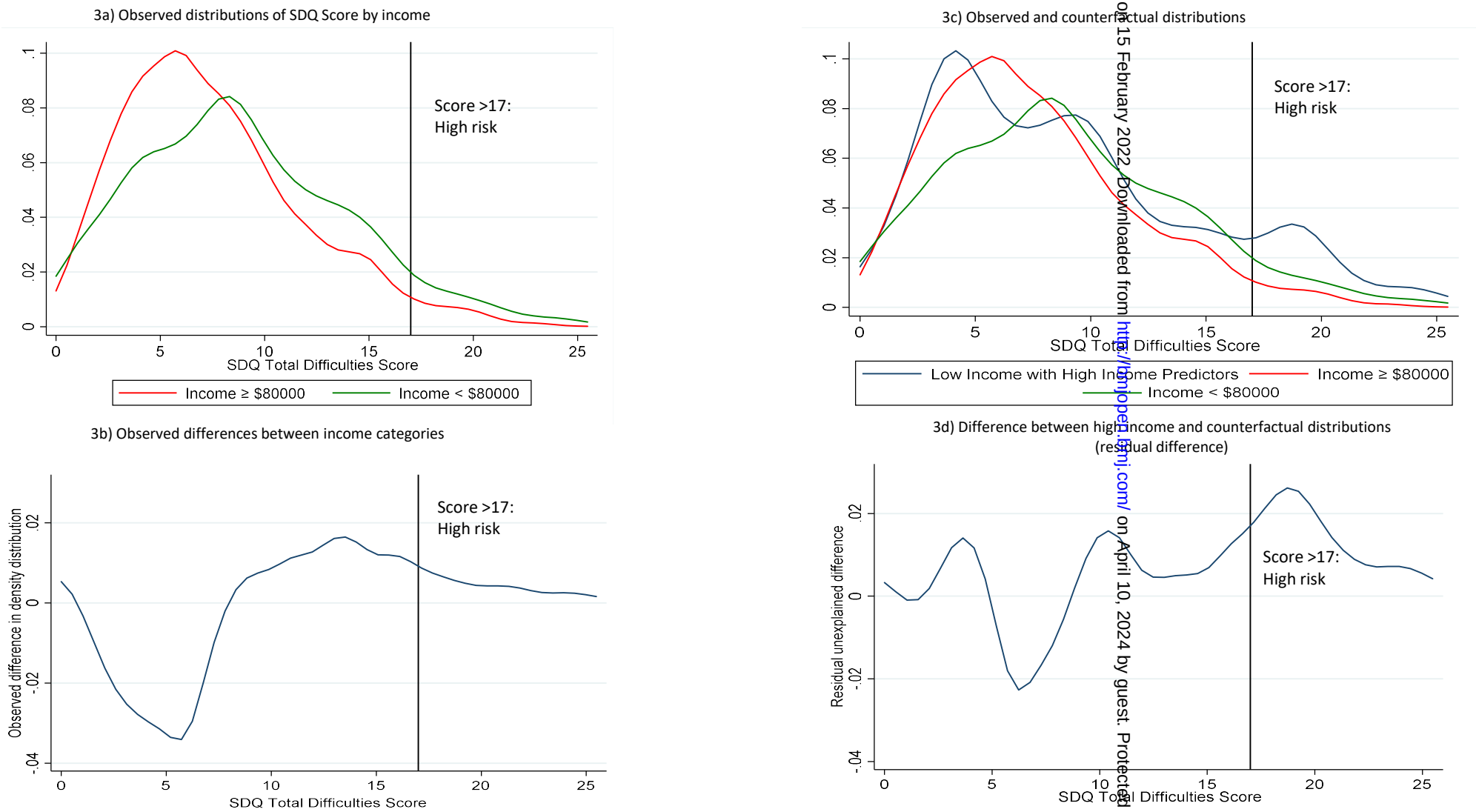
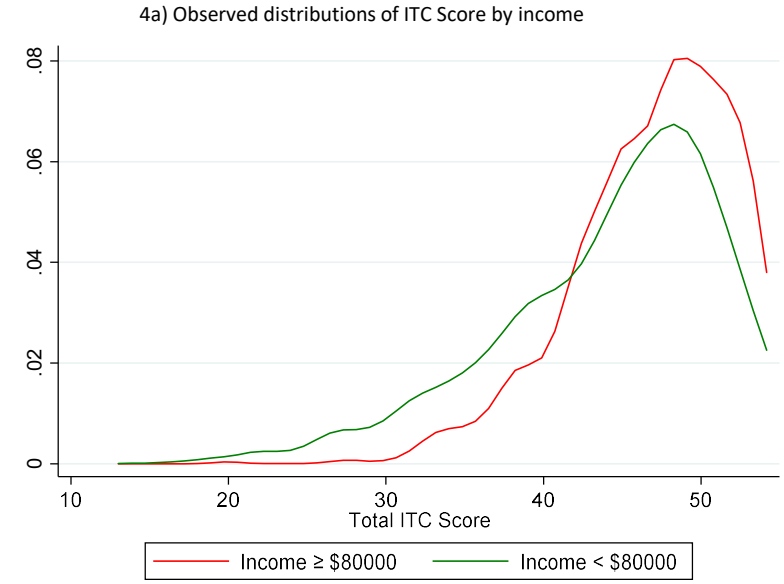
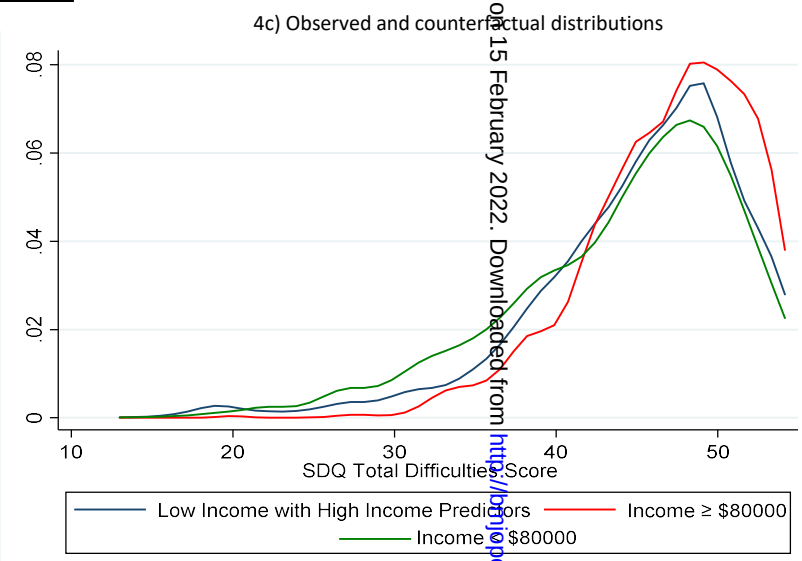
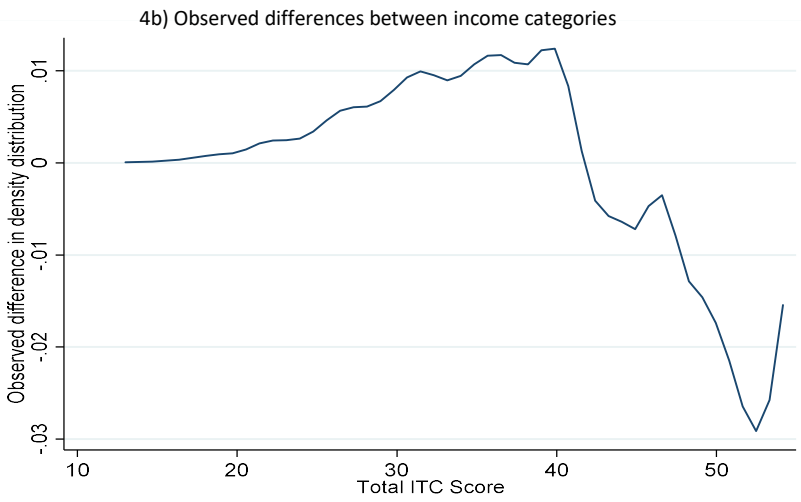
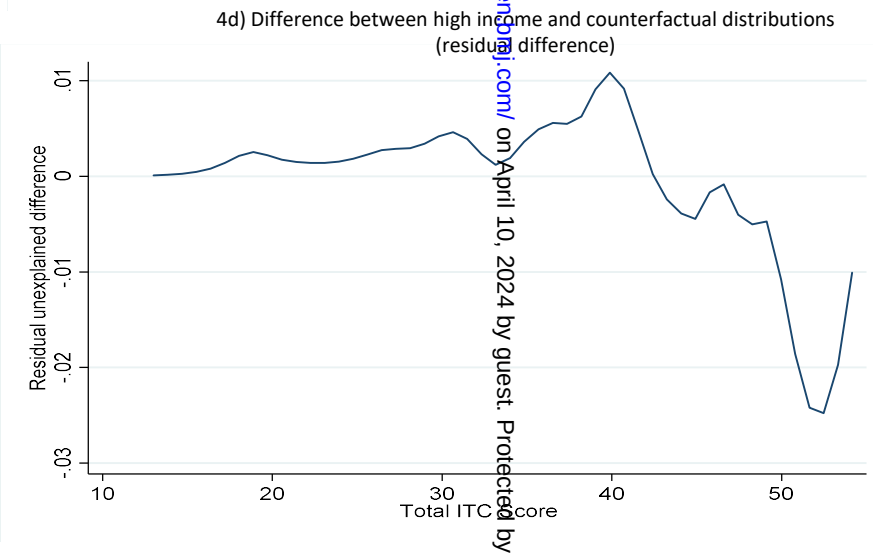


Figure 4: Total ITC Score









Appendix 1

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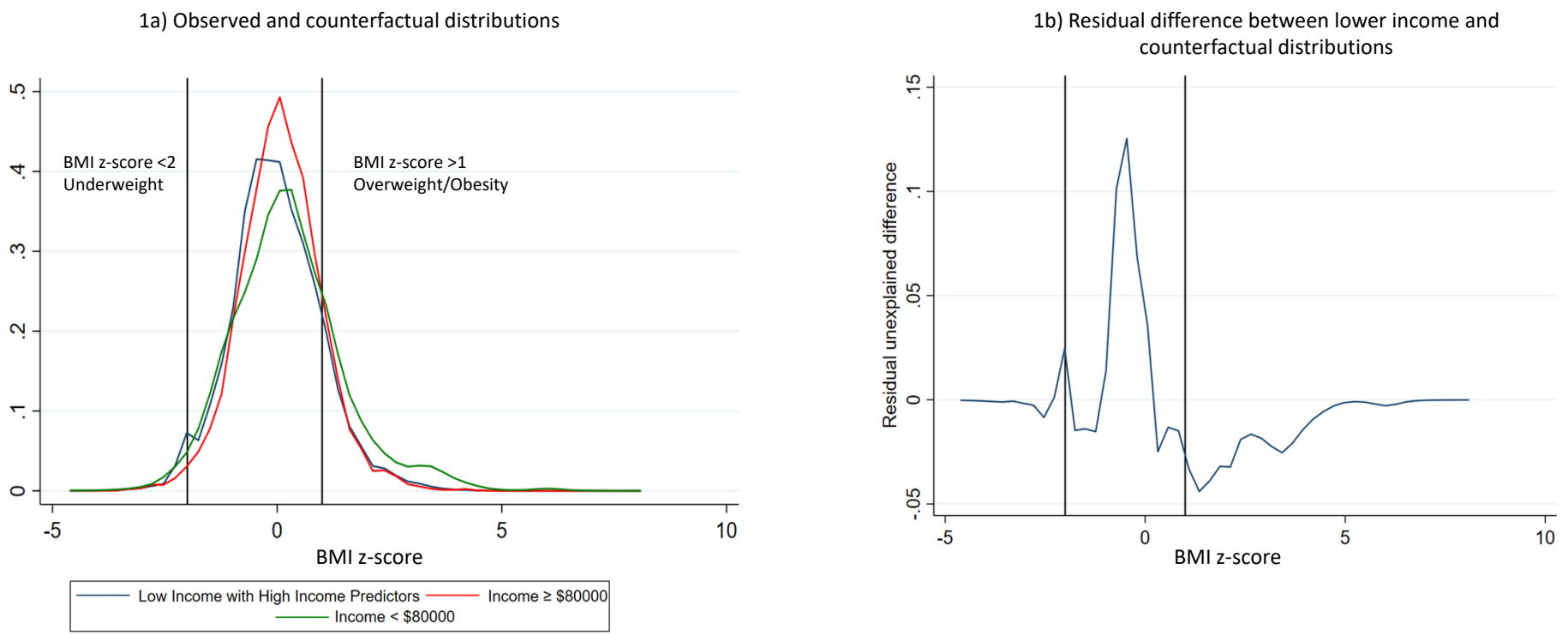
Figure 1: BMI Z-Score Distributional Decomposition

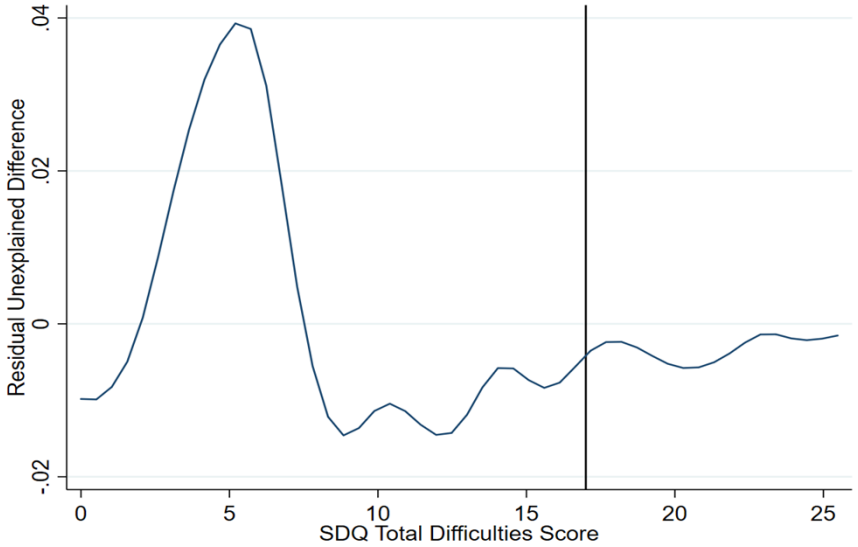


Higher income group re-weighted to have predictor profiles of lower-income group

Figure 2: SDQ Distributional Decomposition

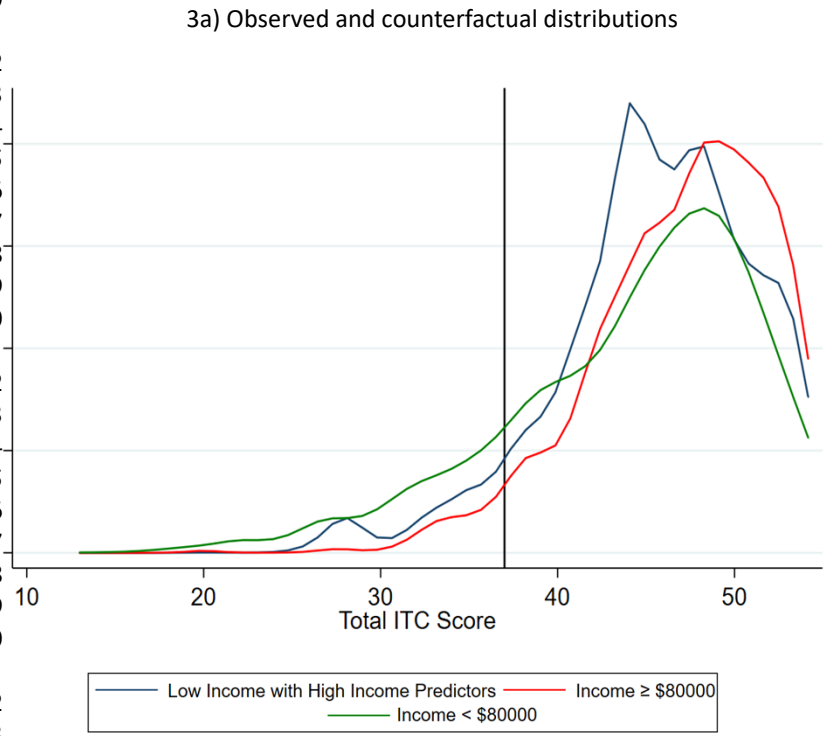
2a) Observed and counterfactual distributions

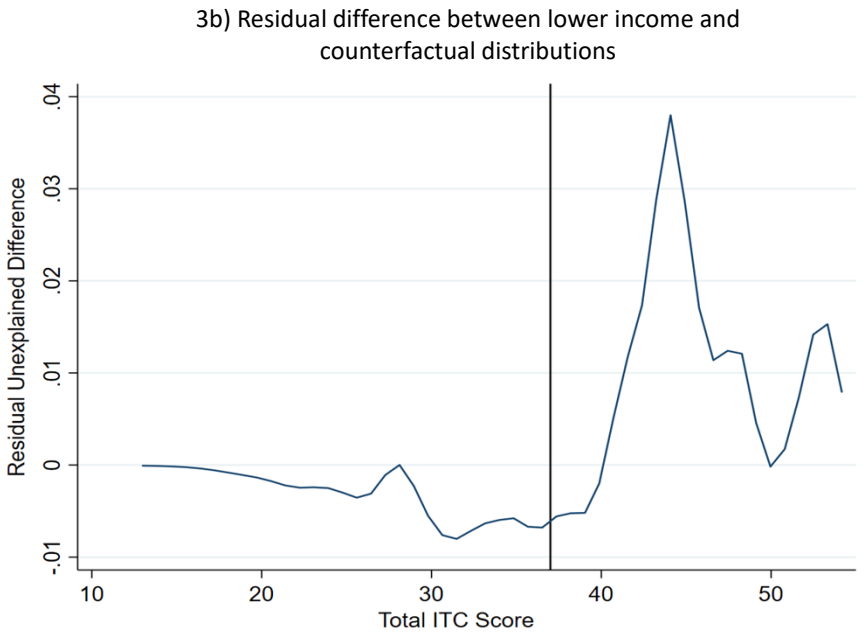
2b) Residual difference between lower income and counterfactual distributions



Higher income group re-weighted to have predictor profiles of lower-income group

Figure 3: ITC Distributional Decomposition





Higher income group re-weighted to have predictor profiles of lower-income group

STROBE Statement—Checklist of items that should be included in reports of ***cross-sectional studies***

	Item No	Recommendation	Page No
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	3
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	3-4
Objectives	3	State specific objectives, including any prespecified hypotheses	4
Methods			
Study design	4	Present key elements of study design early in the paper	5
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	5
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants	5
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	5-7
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	5-7
Bias	9	Describe any efforts to address potential sources of bias	7-8
Study size	10	Explain how the study size was arrived at	8
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	7-8
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	7-8
		(*b*) Describe any methods used to examine subgroups and interactions	7-8
		(*c*) Explain how missing data were addressed	7-8
		(*d*) If applicable, describe analytical methods taking account of sampling strategy	
		(*e*) Describe any sensitivity analyses	8
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	8, Figure 1
		(b) Give reasons for non-participation at each stage	N/A
		(c) Consider use of a flow diagram	Figure 1
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	9, Table 1
		(b) Indicate number of participants with missing data for each variable of interest	
Outcome data	15*	Report numbers of outcome events or summary measures	Table 1

Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	N/A
		(*b*) Report category boundaries when continuous variables were categorized	N/A
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	N/A
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	
Discussion			
Key results	18	Summarise key results with reference to study objectives	11
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	13-14
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	14
Generalisability	21	Discuss the generalisability (external validity) of the study results	14
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	1

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

BMJ Open

Understanding income-related differences in distribution of child growth, behaviour and development using a cross-sectional sample of a clinical cohort study

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Primary Subject Heading:	Paediatrics
Secondary Subject Heading:	Epidemiology
Keywords:	PAEDIATRICS, SOCIAL MEDICINE, EPIDEMIOLOGY, Community child health < PAEDIATRICS

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Understanding income-related differences in distribution of child growth, behaviour and development using a cross-sectional sample of a clinical cohort study

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Abbreviations:
BMI: Body mass index
SDQ: Strengths and Difficulties Questionnaire
ITC: Infant-toddler checklist

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ABSTRACT

Objectives: Children from low-income households are at an increased risk of social, behavioral, and physical health problems. Prior studies have generally relied on dichotomous outcome measures. However, inequities may exist along the range of outcome distribution. Our objective was to examine differences in distribution of three child health outcomes byincome categories (high versus low): body mass index (BMI), behavior difficulties, and development.

Design and Setting: This was a cross-sectional study using data from a primary-care based research network with sites in three Canadian cities, and 15 practices enrolling participants.

Participants, Independent variable and Outcomes: The independent variable was annual household income, dichotomized at the median income for Toronto (< $80,000 or ≥$80,000 CAD). Outcomes were: 1) growth (BMI z-score (zBMI) at 5 years, 1628 participants); 2) behavior (Strengths and Difficulties Questionnaire (SDQ) at 3-5 years, 649 participants); 3) development (Infant Toddler Checklist (ITC) at 18 months, 1405 participants). We used distributional decomposition to compare distributions of these outcomes for each income group, and then to construct a counterfactual distribution that describes the hypothetical distribution of the low-income group with the predictor profile of the higher-income group.

Results: We included data from 1628 (zBMI), 649 (SDQ) and 1405 (ITC) children. Children with lower family income had a higher risk distribution for all outcomes. For all outcomes, thecounterfactual distribution, which represented the distribution of children with lower-income who were assigned the predictor profile of the higher income group, was more favorable than their observed distributions.

Conclusion: Comparing the distributions of child health outcomes and understanding different risk profiles for children from higher and lower income groups can offer a deeper understanding of inequities in child health outcomes. These methods may offer an approach that can be implemented in larger datasets to inform future interventions.

Strengths and limitations of this study

Strengths of this study include:

- Large sample of young children in a major urban area in Canada
- Use of distributional decomposition offers a novel alternative to simple regression for this population and these outcomes
- All outcomes defined using objective measures or validated instruments relevant to clinical practice

Limitations of this study include:

- Limits to generalizability related to lower proportion of children from lower income households and recruitment from primary care practices in an urban setting
- Important predictors for each outcome may not have been included in this analysis

INTRODUCTION

Income is an important determinant of child health, with children living in households from the lowest income quintile experiencing poorer health outcomes on multiple measures.[1] Lower socioeconomic status, the broader construct that speaks to the material and social resources of families that are linked to income and education, has been associated with poorer child health outcomes across domains[2], including increased risk learning disability or serious behavioral difficulty, poorer educational outcomes[3], and mental health challenges.[4]

There is a strong argument in favour of using continuous outcome measures in population health research. While population-level means or categorical definitions of outcomes may show improvement in important health outcomes over time, inequities may be overlooked by not examining the distributions of outcomes.[5] Research findings based on categorized outcomes may be easier to use in clinical practice. However, studying continuous measures can reduce bias that may be introduced with assigning categories and may increase statistical power.[6] Observing differences across the entire distribution may have important health implications but may not be captured in collapsed categories or using standard statistical tests due to smaller sample sizes at the tails of distributions or small but cumulatively important effect sizes. Understanding inequities in the full range of outcome distribution may also provide more nuanced findings to inform specific interventions.[7, 8]

As research in the health sciences strives to generate evidence to support reducing inequities in child health, understanding inequities across the full range of outcome distribution may yield important knowledge that could inform specific targeted or population-level interventions, but may be overlooked using standard methods. However, research examining distributions in child health is extremely scarce. A scoping review exploring the literature assessing birth weight identified a conceptual rationale for studying inequities in distributions,

but a gap in the use of distributions analytically in favour of categorical analyses such as quantile regression.[9] Distributional decomposition is a method which has been used to explore inequities in distribution of outcomes in studies of health outcomes in adults, including body mass and blood pressure.[7, 10] This method offers an opportunity to observe differences between groups across the entire distribution of health outcomes, and then to explore the ways in which possible predictors of the outcome may account for differences observed.

Obesity, mental illness and developmental delays are among the most significant chronic conditions faced by children and they share risk and protective factors,[11, 12] including poverty and childhood adversity.[13] However, there is limited research examining income inequities in very young children, and data from population-based clinical cohorts is scarce. Our first objective was to examine differences in the distribution of three child health outcomes in young children by income: body mass index (BMI), behavior difficulties, and development. Our second objective was to demonstrate how a method called distribution decomposition in order to explore the extent to which differences across the income distribution can be accounted for by common predictors for each outcome.

METHODS

Study Design, Setting and Participants

This was a cross-sectional study of children enrolled in the TARGet Kids! Research Network. TARGet Kids! is a primary care practice-based research network in the Greater Toronto Area and Kingston, Ontario, and Montreal, Quebec. Children less than 6 years old are recruited by trained research personnel embedded at primary care paediatric and family medicine practices. They are followed prospectively into adolescence. Participants complete standardized questionnaires and have anthropometrics measured at scheduled healthcare maintenance visits

and are followed yearly. The sample used for this analysis includes outcomes collected from 2008-2019. The study protocol and sample population have been described in detail.[14]

Exclusion criteria at enrollment are health conditions affecting growth, severe developmental delay, chronic health conditions (except asthma and high functioning autism), birth less than 32 weeks' gestation and families unable to complete questionnaires in English. This study was approved by the Research Ethics Board at the Hospital for Sick Children (REB # 1000012436), Unity Health Toronto, and McGill University.

Patient and Public Involvement

The TARGet Kids! Research Network includes a Parent and Clinician Team (PACT) which is actively involved in guiding the research directions and priorities of TARGet Kids!.[15]Parents and patients were not actively involved in the design of this secondary analysis of existing TARGet kids! data. Results are disseminated to study participants through study communications and the TARGet Kids! website.

Study Assessments

Independent Variable

The independent variable was parent-reported annual household income. It is collected in the standardized TARGet Kids nutrition and health questionnaire with a single question, "what was your family income before taxes last year," with 13 response categories, ranging from "less than $10,000" to "greater than $500,000." We created two categories, dichotomized at approximately the median household income in the Toronto Census Metropolitan Area based on the 2016 Canadian census (< $80,000 or ≥$80,000 CAD).We dichotomized at the median income.[16] We selected this cut point to represent a common measure of household income, and to ensure a robust sample size in both groups to permit the analysis.

Dependent Variables

Dependent variables were: 1) growth (body mass index z-score (zBMI) at 5 years); 2) child behavior (total difficulties score on the Strengths and Difficulties Questionnaire (SDQ) at 3-5 years); 3) development (total score on the Infant Toddler Checklist (ITC) at 18 months).

To assess zBMI, height and weight were measured by trained research assistants according to standard protocols.[17] BMI was calculated as weight in kilograms divided by squared heighted in meters and measured at 5 years old. Age and sex standardized zBMI was calculated using the recommended WHO growth standards.[18]

To assess child behavior, we used the Strengths and Difficulties Questionnaire (SDQ) total difficulties score, measured between 3 and 5 years of age. The SDQ has been validated in children of all ages and across multiple countries and cultural groups.[19, 20] The score is comprised of 20 questions, and measures emotional problems, conduct problems, hyperactivity, and peer problems. Higher score indicates greater difficulties.

To assess child development, we used the Infant Toddler Checklist (ITC – also known as the Communication and Symbolic Behavior Scales: Developmental Profile), measured between 18 and 24 months.[21, 22] This is a measure for clinical screening of social and communication developmental risk, validated for use between 6 and 24 months. Lower score indicates greater developmental risk.

Covariates

Child and maternal characteristics were used to produce predictor profiles. We selected these predictors to represent confounders commonly included in adjusted regression models and other analyses within the literature more broadly. For children, these were age (months), sex, birthweight (kilograms), and living arrangement (living with both parents, or any other

arrangement) for all models; gestational age (32 to 36 weeks, 37 weeks and greater) was included for ITC models only as an important predictor of development.[23], and total months breastfed. For mothers, these were maternal age (years), education (high school or less, university or more), immigration status (born in Canada, born outside of Canada), ethnic ancestry (European/White, other) and body mass index (kg/m^2). Breastfeeding duration, and maternal BMI were included in the BMI models only as important predictors of child BMI.[24]

Statistical Analysis

We used descriptive statistics to characterize the study population and describe the means and proportions of the outcomes of interest. We used Mann-Whitney and chi-square tests to compare predictors by income category. We used Kolmogorov-Smirnov tests to assess differences between distribution curves for each outcome. Using methods described by Siddiqi et al[7], who adapted the DiNardo-Fortin-Lemieux decomposition[25], we then measured the *distributional inequality.* We first estimated the probability densities of each outcome for each income subgroup using an adaptative kernel estimator. We then calculated d*istributional inequality* as the difference between the kernel density estimates of the two income subgroups. At any given point, it measures the difference between proportion of children in the lower-income group and those in the higher income group. We depicted the kernel density distributions and the distributional inequality graphically.

We then proceeded with *distributional decomposition* separately for each outcome. Distributional decomposition offers a method to identify the proportion of inequality at each point in the outcome distribution that can be explained by a set of common predictors using a simple reweighting method originally developed by DiNardo et al.[25] The syntax for this specific

analysis using Stata was developed and refined by members of our team (V. Hildebrand). We estimated the counterfactual density function for each outcome of the lower-income group that would prevail were children in the lower-income group given the predictors of the higher income group. This involves reweighting the density function of the lower-income group such that the reweighted sample of children in the lower-income group has the same predictors of the children in the higher income group.[7, 25] We then used the counterfactual weight to reweight the kernel density estimates to produce the counterfactual distribution. This counterfactual density distribution demonstrates how the observed distribution of the children in the lower-income group would change if they took on the predictor profile of children in the higher-income group. We plotted this re-weighted counterfactual distribution to compare it visually to the original distributions for the higher- and lower-income groups.

Because of smaller numbers of children at the high and low ends of the distributions of each variable for the lower-income group, we undertook a sensitivity analysis, reversing the re-weighting by applying the predictor profile of the lower-income group to the higher-income group. This increases the likelihood of achieving "common support", where all configurations of predictor profiles of the re-weighted group are present in the reference group. We would expect the distribution to appear like the inverse of the first one.

As an additional analysis, to examine associations between income and each outcome, we also performed unadjusted and adjusted multinomial regression analyses. For zBMI, we used a four-category outcome based on clinical risk stratification and defined the variable as BMI z-score less than -2, greater than or equal to -2 to 1, greater than or equal to 1 to 2, and greater than or equal to 2. For zBMI, the reference group was set as the second category (normal weight

status). For SDQ and ITC scores, we divided the total score into quartiles. For these outcomes, the reference group was set to the first quartile.

Statistical analyses were performed using Stata (v 14.2, College Station, Texas).[26]

RESULTS

For the BMI outcome 2,123 children between 60 and 71 months had complete outcome and income reported, of whom 1,628 (76 % of total) had complete information for all variables and were included. For our SDQ cohort, 774 had complete outcome and income reported, 649 (84% of total) of whom had complete information for each variable and were included. For our ITC cohort, 1698 had complete outcome and income reported, 1405 (81% of total) of whom had complete information for each variable and were included (Figure 1).

The predictor profiles of children from higher and lower-income households are shown in Table 1. Children from lower-income households had a shorter duration of breastfeeding, had mothers who were younger; a lower proportion lived with both parents, had fewer mothers with a university education; a greater proportion had mothers who were immigrants to Canada or reported ethnic ancestry as other than European.

Body Mass Index

A greater proportion of children with higher income were in the normal weight category compared with children with lower-income (84.9% vs 77.4%), while a greater proportion of children with low income were in the underweight, overweight, and obesity categories (Table 1). KST test showed evidence of statistically significant difference between distributions income groups (p=0.004). Comparing the density distributions by income category, the distribution of children with high income was more concentrated around a zBMI of zero, while a higher

proportion of children with low-income were at the tails of the distribution (Figure 2a). Figure 2b shows the difference between the observed distributions.

When children from lower-income households were re-weighted to have the predictor profiles of children from higher-income households, the distribution of zBMI within the normal range (-1 to 1) narrowed. This re-weighted distribution is shown with the observed distributions in Figure 2c. The residual, unexplained difference between the re-weighted distribution and the higher-income distribution is shown in Figure 2d. In this normal range, the difference between the re-weighted distribution for children from lower-income households and the distribution of children from higher-income households decreased substantially (Figure 2d). However, at the tails of the distribution, the re-weighted distribution curve was largely unchanged from the observed distribution.

Strengths and Difficulties Questionnaire

Children from higher-income households had a lower mean SDQ score (7.2 vs 9.0) (table 1). KST test showed evidence of statistically significant difference between distributions income groups (p=0.002). Comparing the density distributions by income category, the differences in distribution were most notable in the lower and middle range of the score distribution, which had a lower proportion of children from lower-income households (Figure 3a). There was a greater proportion of children from lower-income households in the high- risk range (>17) as well. Figure 3b shows the difference between the observed distributions.

The re-weighted distribution of SDQ total difficulties score for children from lower-income families in the low-risk range shifted to the left, with a greater proportion having even *lower scores* than before. This re-weighted distribution is shown with the observed distributions in Figure 3c. The residual distribution had two peaks in the low-risk range, which were higher

than the observed distribution for children from higher-income households, and a third peak in the high-risk range. The residual, unexplained difference between the re-weighted distribution and the high-income distribution is shown in Figure 3d.

Infant-Toddler Checklist

Children from higher-income households had a higher mean ITC score indicating lower risk (46.6 vs 44.5) (table 1). KST test showed evidence of statistically significant difference between distributions income groups ($p<0.001$). Comparing density distribution by income, the differences were notable across the distribution, with a greater proportion of children from lower-income households in the higher risk range (Figure 4a). Figure 4b shows the difference between the observed distributions.

The re-weighted distribution of ITC score for children from lower-income households shows that the distribution in the low-risk range (higher scores) is like the observed distribution from high income households, indicating that common predictors explain much of the difference. This re-weighted distribution is shown with the observed distributions in Figure 4c. However, as total ITC score decreases into higher risk ranges, the re-weighted distribution still shows a greater proportion of children from low-income households with lower scores. The residual, unexplained difference between the re-weighted distribution and the high-income distribution is shown in Figure 4d.

Sensitivity Analyses

Our sensitivity analysis, presented in supplement 1, which re-weighted the predictor profiles of children from higher-income households to have the predictor profile of children from lower-income households, showed a generally similar pattern in the low-risk range of the distribution for each outcome. Most notably, for SDQ, this analysis resolves the second peak of

unexplained difference in the high-risk range, suggesting this may be due to low sample size in the lower-income group at the high end of the distribution.

Multinomial regression models for each outcome are found in supplement 2. The models generally demonstrate that lower income is associated with higher zBMI, higher SDQ Total Difficulties Score score, and lower ITC score. There was evidence of confounding by the covariates included.

DISCUSSION

In this study with a large cohort of young children, we found that there were notable differences in the distributions of children from higher and lower-income households for three important outcomes studied: zBMI, total behavioral difficulties, and developmental risk, with a greater proportion of children with higher-income in the low-risk range of the distribution, and a greater proportion of those with lower-income in the higher risk range. When the distributions for children with lower-income were re-weighted to give them the predictor profiles of children with higher-income children, children with lower-income already in the low-risk range adopted a distribution that appeared to be *even lower risk.* After re-weighting, children in the lower-income group with behavioral and developmental outcomes in the high-risk range adopted a distribution with a lower proportion of children at high risk. This was not the case for zBMI, where the re-weighted distributions were like the observed distributions. Comparing observed distributions, the difference between income categories in the higher risk ranges (obesity, underweight) are smaller than the differences in the lower risk range (normal weight).

By comparing the observed distributions of continuous measures of child health by income, we can appreciate inequalities that may not be captured using categorical definitions that are used for clinical risk stratification. Categorical measurement can collapse variation within

each category, and this variation can yield important information. These inequalities may have clinical meaning; for example, small differences in SDQ score or in zBMI are related to differences in long-term behavior and cardiometabolic outcomes, respectively.[27, 28] Small differences in risk early in life may continue to grow through the life-course. For example, higher BMI in early life is associated with greater risk of obesity later.[29] While the multinomial regression analyses generally support the differences observed in distributions, visualizing the distributions offers a clearer picture of differences in the distribution, including transition points, for example, when distribution curves cross. Comparing distributions offers the opportunity to disaggregate differences that may not be appreciated with categorical outcome definitions.

The distributional decomposition analysis adds a further layer to our understanding of potential explanations for these inequities. For all outcomes, we found that the inequality between the observed distribution of children with higher-income and the counterfactual distribution was lower than the inequality between observed distributions of children within the "low-risk" range of the distribution. However, in the higher risk range, the counterfactual reduced the inequality to a variable degree depending on outcome. We suspect that the determinants of having clinically meaningful concerns about growth, behavior or development are different than the determinants of where an individual falls in the lower risk range. For example, clinically significant behavior difficulties on the SDQ may represent an underlying behavior disorder such as attention-deficit disorder, while within the low-risk range, other factors such as parenting behaviors, which are more closely related to predictors in our predictor profiles, may be more influential.

For zBMI, the counterfactual distribution demonstrates that routine predictors of BMI explain some of the income-related inequality in the distribution within the normal range but

does not explain the inequalities observed for children with obesity and underweight. It is possible that the determinants of obesity could be different than the determinants of underweight[30], or that low income is a primary driver of BMI.[31, 32]

Compared to zBMI, routine predictors of child behavior and mental health can explain more of the income-related inequality in the distribution of SDQ score, including at the higher range of the distribution. The highest risk range of the distribution may have represented children with significant morbidity, which likely has different predictors than a lower score. Our sensitivity analysis, which re-weighted the children with high-income to have predictors of children with low-income, resolved this issue, suggesting sample size in the distribution of predictors for the lower-income group may be a contributor. The counterfactual distribution of the ITC was the closest to the observed distribution of children with higher-income of the three child health outcomes studied. It is possible that ITC had the strongest income-related predictors of the outcome included in the model, with parental education as a particularly important driver of parent-toddler communication, promoting language development.[33]

This study has several strengths. It includes a large sample of young children in a major urban area in Canada and employs a novel and revealing analysis. All outcomes were defined using objective measures (zBMI) orvalidated instruments (SDQ and ITC), which are relevant to clinical practice. This study also has certain limitations. Our sample had a lower proportion of children in the lower-income group, and particularly at the tail ends of distributions where there were fewer children overall, fewer children with each covariate pattern may have led to reduced robustness of the re-weighted counterfactual. Future research could explore alterative categories of income. There was a smaller proportion of participants with certain characteristics which required categorization of certain predictors and did not allow for stratification by potentially

important predictors (eg. race/ethnicity). Children with missing data may come from households with low-income or other stressors and are not represented. Furthermore, as our sample was drawn from a clinical setting, our recruitment and data collection process may have led to selection bias, with children from low-income families with poorer health over-represented compared to those with better health. This study is cross-sectional and causality cannot be inferred. Importantly, the relationship between income and health is likely bi-directional; while low-income may lead to poorer health outcomes, there is also evidence to suggest that chronic illness in childhood has adverse impacts on family income.[34] One further consideration is the possibility that predictors of each outcome are also predictors of income (such as maternal education). In this case, some of the effects of income may actually be caused by these predictors. It is also likely that there are other meaningful predictors of each outcome that were not included in our predictor profile and may be important to the relationship between income and each outcome. For example, variables such as number of children in household, parenting styles and diet quality could be related to both income and outcome. Future research could explore a more detailed conceptual model of income-related predictors of each outcome to shed light on additional variables and incorporate longitudinal data to better understand causal relationships. Finally, the study takes place in primary care practices in a major urban area in Canada, participating families had higher income, were English-speaking, and may not be representative of children who lack access to primary care, live in rural areas, or who have other barriers to participation in a longitudinal study. Future research should seek out populations of children who are under-represented in these analyses.

CONCLUSIONS

This study examining income-related differences in child growth, behavior, and development found that there were differences in the distribution of each outcome between children from higher and lower-income families, with children from lower-income families showing a higher risk profile. Common predictors of each outcome partially explained the inequality, most notably in the low-risk range. These findings have important implications for health policies and interventions targeting income-based health inequities. Identifying that inequities likely have different predictors across the distribution suggests that future research should further explore predictor profiles that can explain income-related inequities in child health outcomes with a broader scope. It is possible that interventions to reduce inequities by addressing common predictors may improve outcomes in the low-risk range. However, targeted interventions addressing income specifically, as well as the circumstances experienced by families with low-income, may be for those at high risk.

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Figure Captions

Figure 1: These flow diagrams show cohort definitions for each outcome and reasons for participant exclusion due to missing data.

Figure 2:
Distributions and distributional decomposition of BMI z-score, including observed distributions of BMI z-score by income (2a); differences between observed distributions (2b); observed distribution plus the counterfactual distribution of the low-income group with predictor profile of high-income group (2c); and the residual difference between the high-income and counterfactual distributions (2d).

Figure 3:

Distributions and distributional decomposition of SDQ Total Difficulties Score, including observed distributions of Total Difficulties Score by income (3a); differences between observed distributions (3b); observed distribution plus the counterfactual distribution of the low-income group with predictor profile of high-income group (3c); and the residual difference between the high-income and counterfactual distributions (3d).

Figure 4:

Distributions and distributional decomposition of Total ITC Score, including observed distributions of ITC Score by income (4a); differences between observed distributions (4b); observed distribution plus the counterfactual distribution of the low-income group with predictor profile of high-income group (4c); and the residual difference between the high-income and counterfactual distributions (4d).

Ethics Statement:

This study was approved by the Research Ethics Board at the Hospital for Sick Children (REB # 1000012436), Unity Health Toronto, and McGill University.

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Table 1: Participant characteristics and outcomes by income category for each outcome cohort

Characteristic, n (%)	BMI[1] (n= 1,628)			SDQ[2] (n=649)			ITC[3] (n=1405)		
Predictors	Full Sample	Income ≥ $80000 (n=1180)	Income < $80000 (n=448)	Full Sample (649)	Income ≥ $80000 (n=539)	Income < $80000 (n=110)	Full Sample (n=1405)	Income ≥ $80000 (n=1106)	Income < $80000 (n=299)
Child									
Age (months) (mean, SD)	62.6 (2.8)	62.5 (2.7)	62.8 (3.0)	47.5 (12.3)	47.1 (12.3)	49.6 (12.2)	18.6 (0.98)	18.6 (0.97)	18.6 (1.0)
Sex									
Female	795 (48.8)	574 (48.6)	221 (49.3)	323 (49.7)	277 (51.4)	46 (41.8)	638 (45.3)	491 (48.5)	145 (48.5)
Male	833 (51.2)	606 (51.4)	227 (50.7)	326 (50.2)	262 (48.6)	64 (59.2)	614 (45.6)	615 (51.5)	154 (51.5)
Birthweight (kg) (mean, SD)	3.3 (0.6)	3.3 (0.6)	3.2 (0.7)	3.2 (0.6)	3.2 (0.6)	3.1 (0.6)	3.3 (0.7)	3.3 (0.7)	3.2 (0.7)
Gestational Age <37 weeks							189 (13.5)	147 (13.3)	42 (14.1)
Total Months Breastfed	12.6 (9.8)	12.9 (9.1)	12.0 (11.4)						
Lives with Both Parents	1497 (92.0)	1134 (96.1)	363 (81.0)	620 (95.5)	522 (96.8)	98 (88.7)	1346 (95.8)	1091 (97.7)	265 (88.3)
Parent									
Maternal Age at Birth (mean, SD)	33.3 (4.5)	33.9 (3.9)	31.6 (5.6)	33.6 (4.2)	34.0 (3.9)	31.7 (4.8)	33.9 (4.1)	34.4 (3.7)	32.2 (4.9)
Maternal Education									
University or more	1491 (91.6)	1138 (96.4)	353 (78.8)	534 (82.3)	476 (88.3)	58 (52.7)	1154 (82.1)	993 (99.8)	161 (53.9)
High school or less	137 (8.4)	42 (3.6)	95 (21.2)	115 (17.7)	63 (11.7)	52 (47.3)	251 (17.9)	113 (10.2)	138 (46.2)
Maternal BMI	24.7 (4.9)	24.3 (4.5)	25.7 (65.8)						
Mother Born in Canada									
Yes	1114 (68.4)	906 (76.8)	208 (46.4)	436 (67.2)	403 (74.8)	33 (30.0)	978 (69.6)	844 (76.3)	134 (44.8)
No	514 (31.6)	274 (23.2)	240 (453.6)	213 (32.8)	136 (25.2)	77 (70.0)	427 (30.4)	262 (23.7)	165 (55.2)
Maternal Ethnicity									
White/European	1162 (71.4)	909 (77.0)	253 (56.5)	390 (60.1)	353 (65.5)	37 (33.6)	886 (63.6)	766 (69.3)	120 (40.1)
Other	466 (28.6)	271 (23.0)	195 (43.5)	259 (39.9)	186 (34.5)	73 (66.4)	519 (36.9)	340 (30.7)	(59.9)
Outcomes									
BMI z-score Category (n, %)									
< -2.0 (underweight)	25 (1.2)	17 (1.1)	8 (1.3)						
≥-2.0 – <1.0 (normal)	1760 (82.3)	1276 (84.9)	471 (77.4)						
>1.0 – <2.0 (overweight)	273 (12.8)	175 (11.6)	96 (15.5)						
≥ 2.0 (obesity)	80 (3.7)	36 (2.4)	44 (7.1)						
SDQ Score (mean, SD)				7.5 (4.5)	7.2 (4.2)	9.0 (5.2)			
ITC Score (mean, SD)							46.6 (5.8)	47.4 (5.1)	44.5 (7.0)

[1] BMI: Body Mass Index; [2] SDQ: Strengths and Difficulties Questionnaire; [3] ITC: Infant Toddler Checklist

Figure 1: Defining the Cohorts

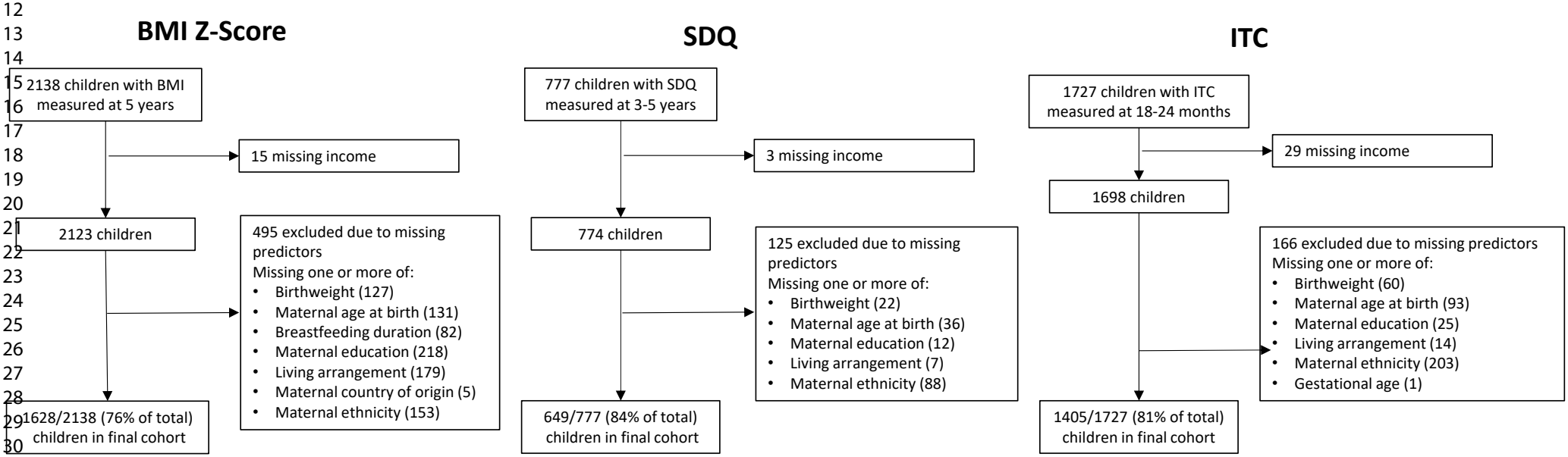


Figure 2: BMI z-score

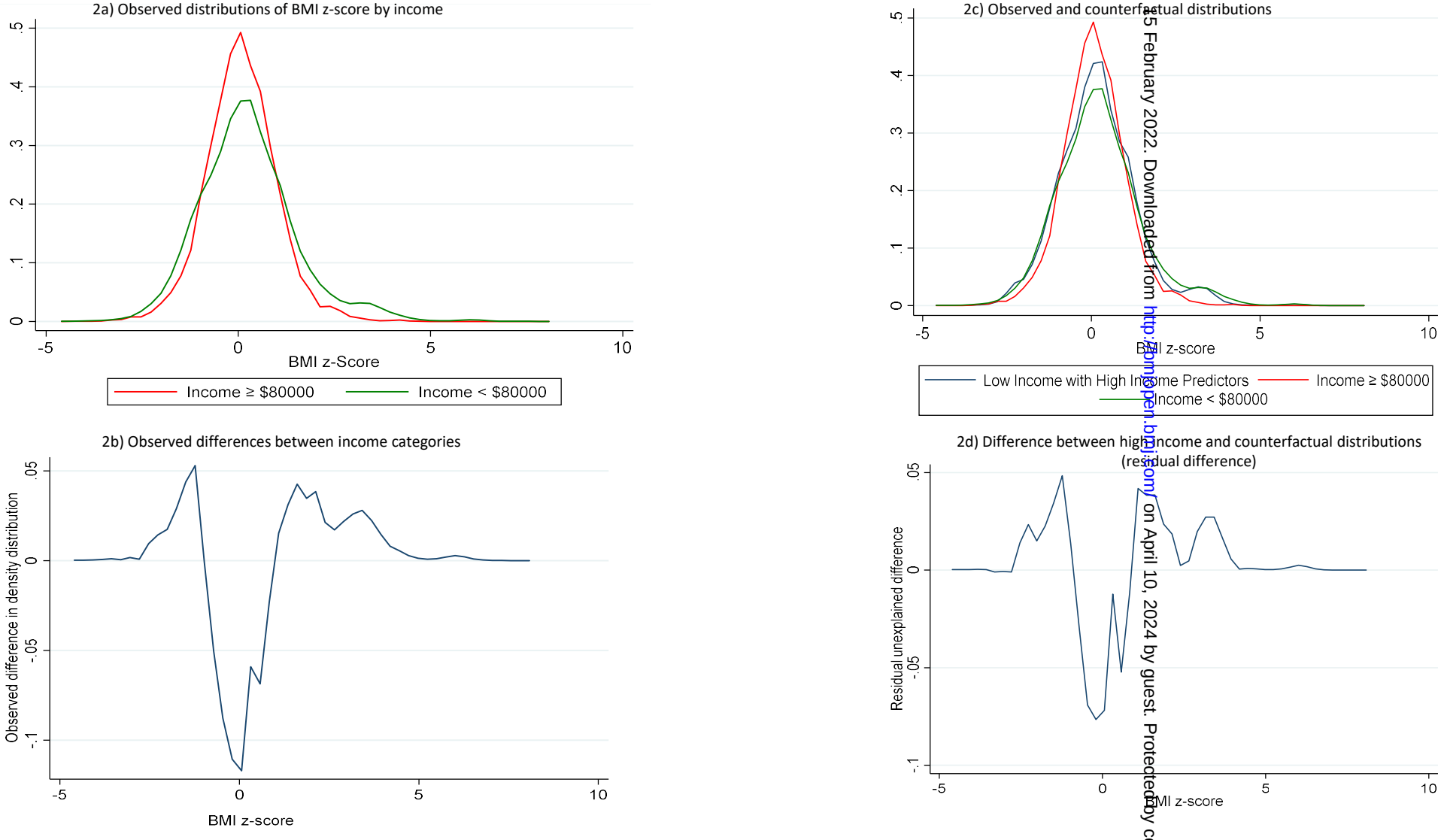
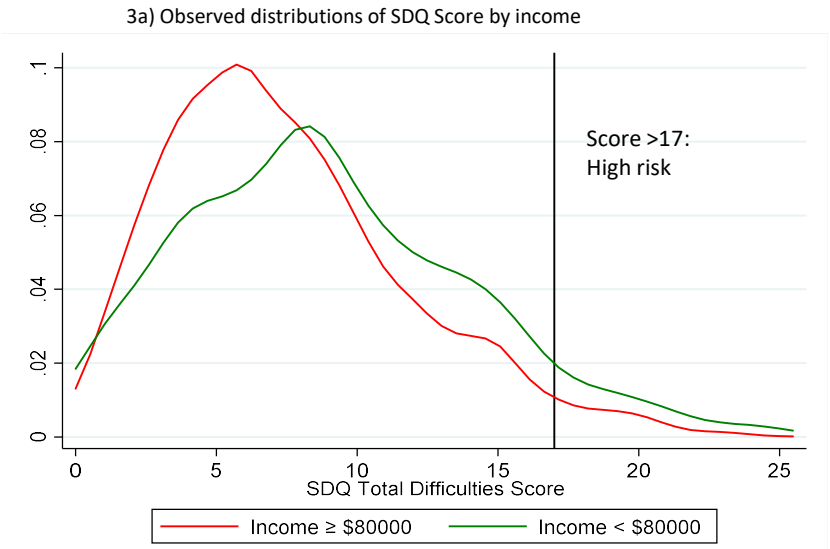
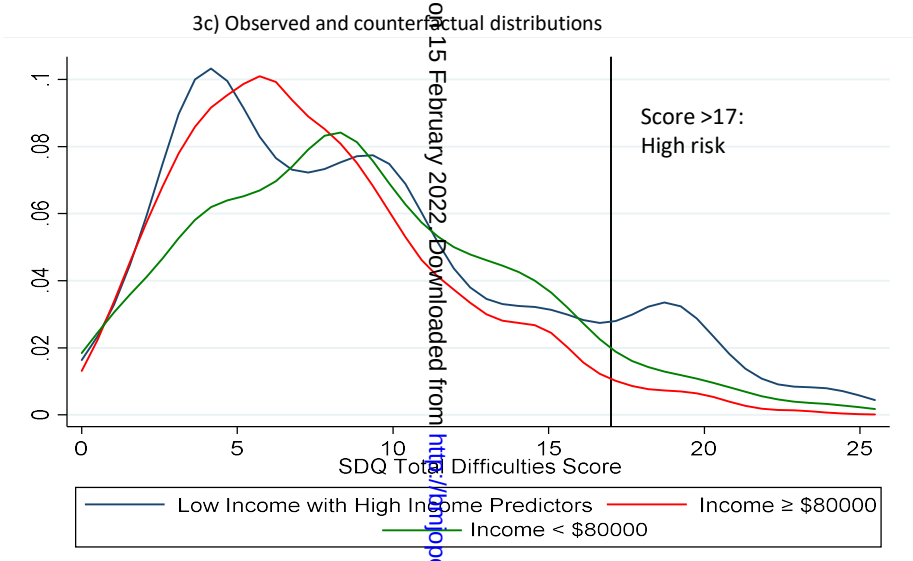
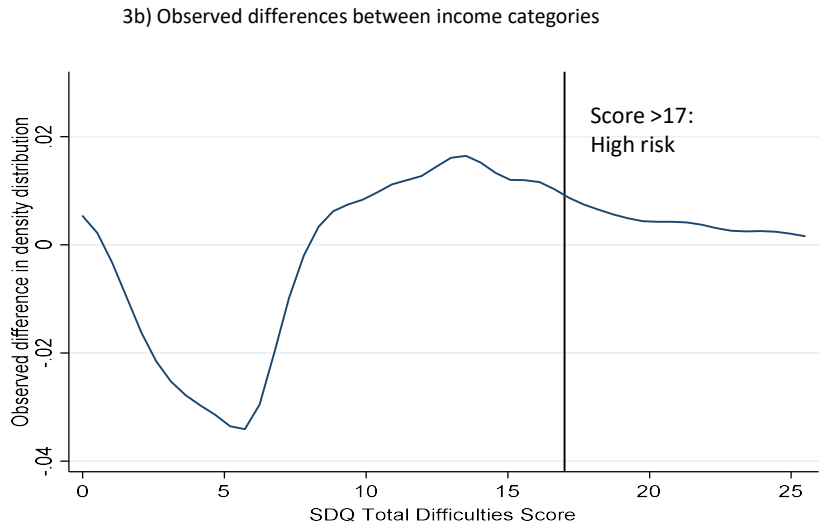


Figure 3: SDQ Total Difficulties Score







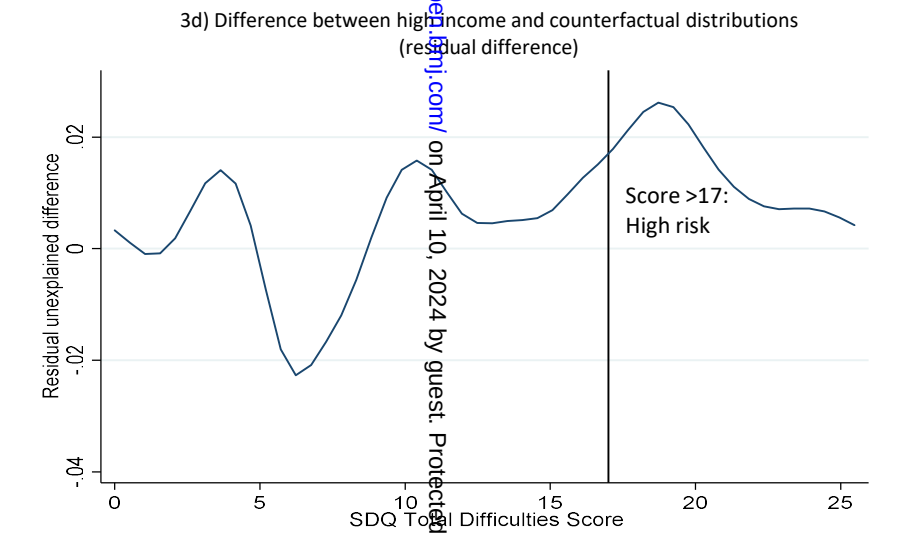
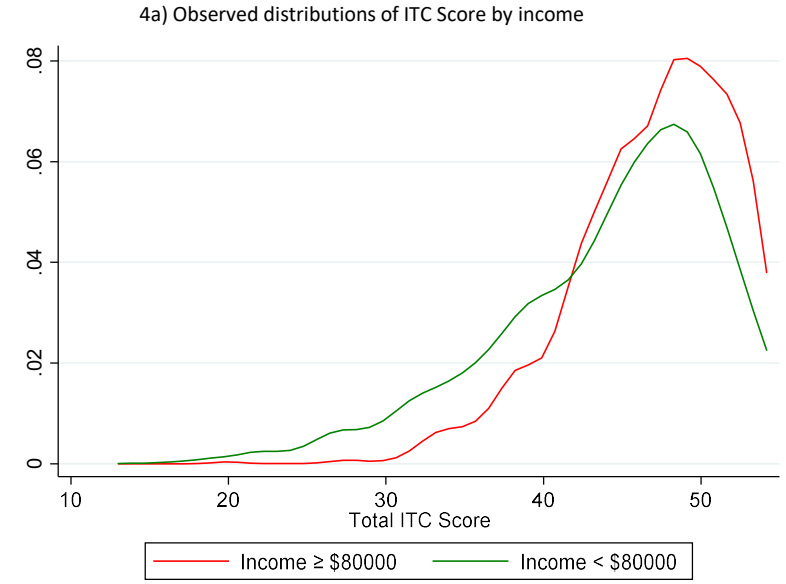
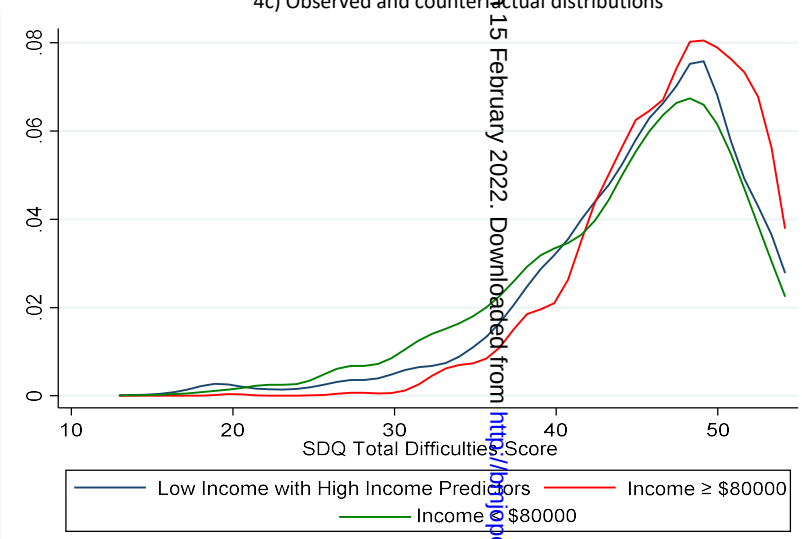
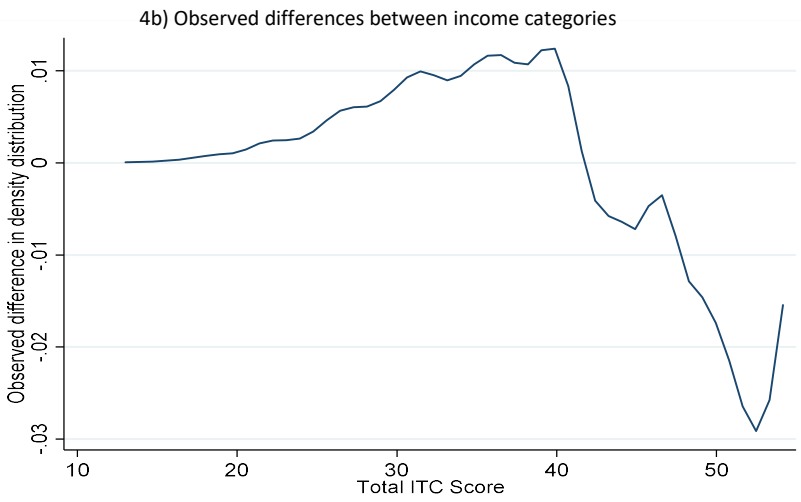


Figure 4: Total ITC Score







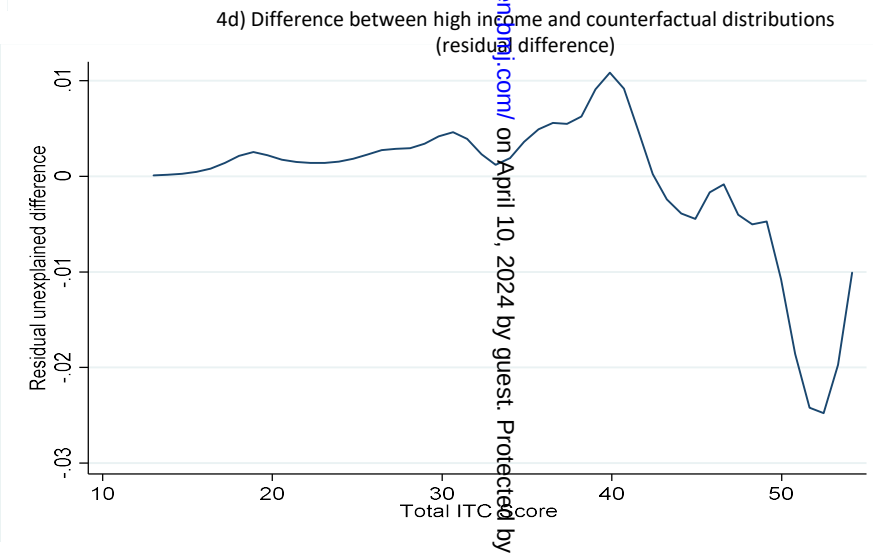
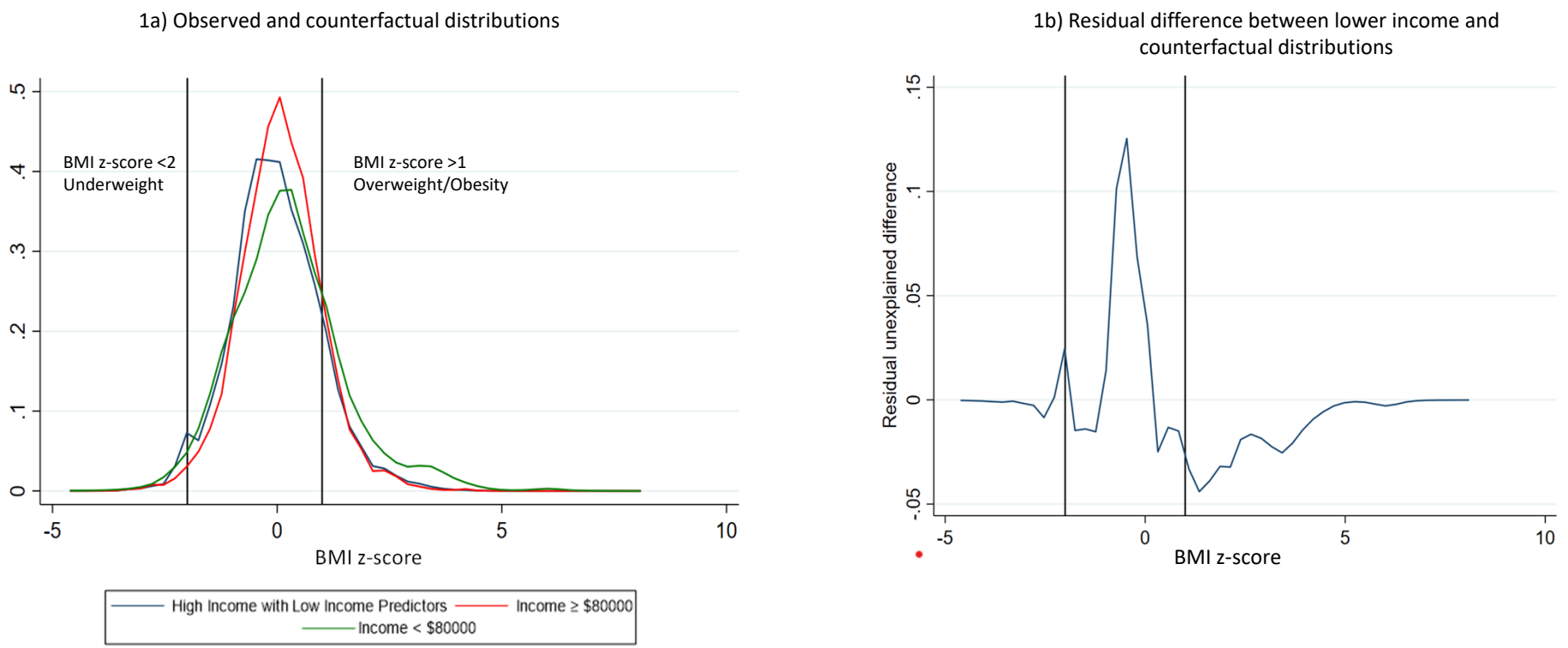


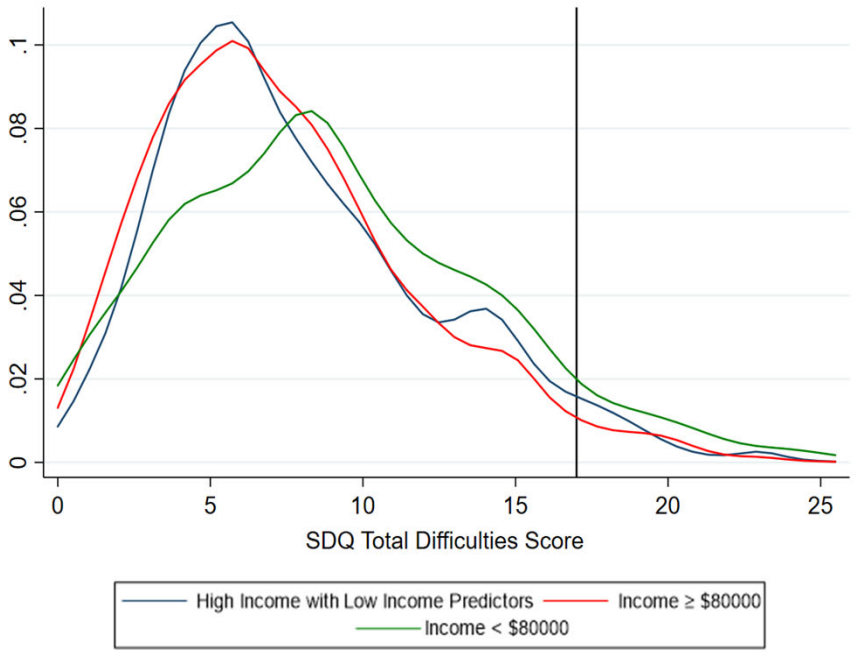
Figure 1: BMI Z-Score Distributional Decomposition



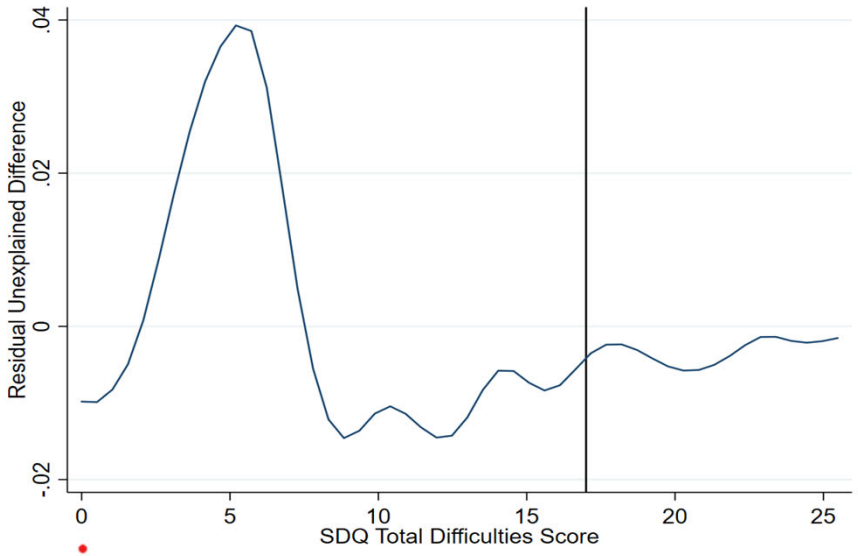
Higher income group re-weighted to have predictor profiles of lower-income group

Figure 2: SDQ Distributional Decomposition

2a) Observed and counterfactual distributions



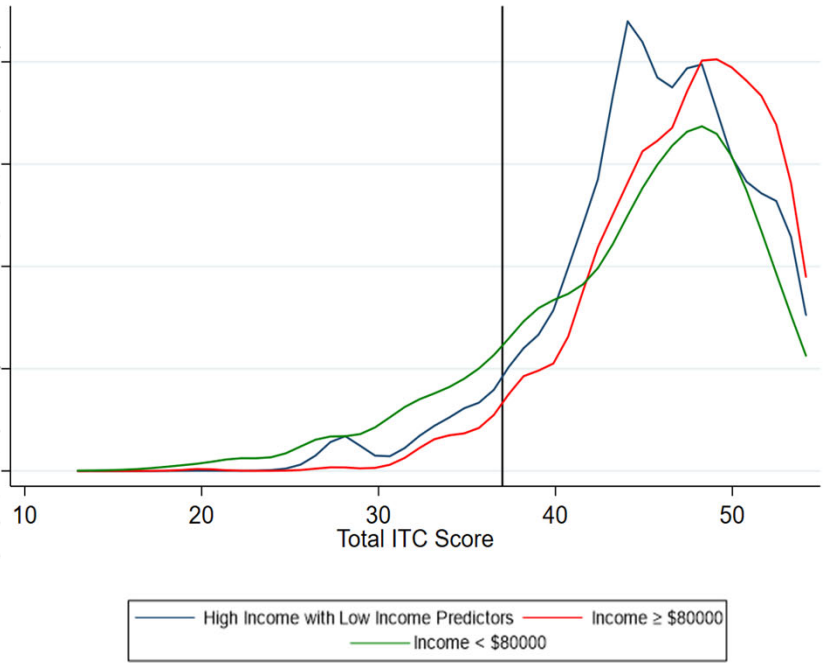
2b) Residual difference between lower income and counterfactual distributions



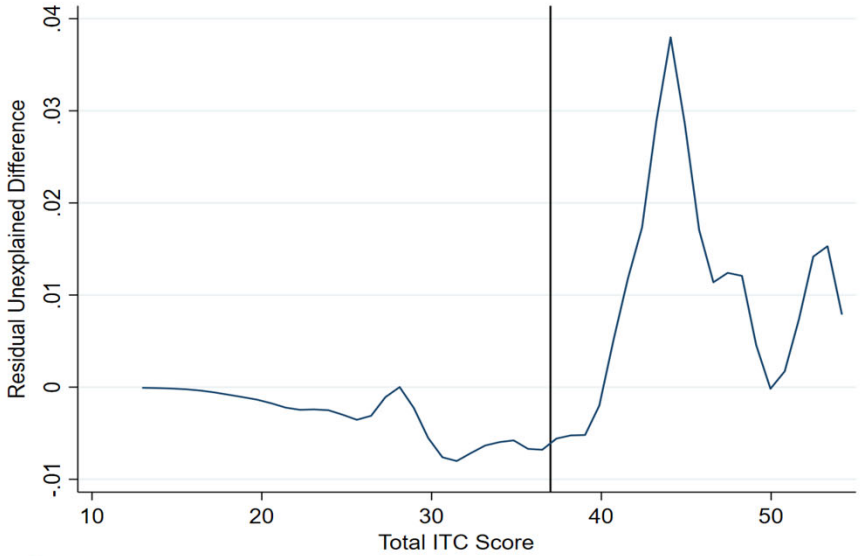
Higher income group re-weighted to have predictor profiles of lower-income group

Figure 3: ITC Distributional Decomposition

3a) Observed and counterfactual distributions



3b) Residual difference between lower income and counterfactual distributions



Higher income group re-weighted to have predictor profiles of lower-income group

Supplementary Table 1: Association between Income and Body Mass Index (BMI) z-score

	BMI z-score < -2 "Underweight"[1]	BMI z-score ≥ 1 to 2 "Overweight"[1]	BMI z-score ≥2 "Obesity"[1]
Unadjusted	RRR[2] (95% CI[3])	RRR (95% CI)	RRR (95% CI)
Income <$80,000	1.72 (0.67, 4.40)	1.46 (1.06, 2.01)	4.15 (2.37, 7.27)
Adjusted	RRR (95% CI)	RRR (95% CI)	RRR (95% CI)
Income <$80,000	1.46 (0.50, 4.28)	1.60 (1.11, 2.33)	3.01 (1.56, 5.82)
Child			
Age (months)	1.15 (1.01, 1.32)	0.98 (0.93, 1.04)	0.99 (0.90, 1.08)
Sex (male)	0.77 (0.30, 1.99)	1.14 (0.84, 1.55)	1.81 (0.99, 3.29)
Birthweight (kg)	0.31 (0.18, 0.56)	1.80 (1.38, 2.34)	1.20 (0.76, 1.89)
Total Months Breastfed	1.00 (0.96, 1.05)	0.99 (0.97, 1.01)	0.97 (0.94, 1.01)
Living Arrangement	1.06 (0.41, 2.75)	0.59 (0.37, 0.95)	0.85 (0.45, 1.60)
Parent			
Maternal Age at Birth	1.02 (0.93, 1.11)	0.97 (0.94. 1.00)	0.99 (0.94,1.06)
Maternal Education	2.81 (0.31, 25.27)	0.69 (0.41. 1.15)	0.55 (0.26, 1.17)
Maternal BMI	0.98 (0.88. 1.09)	1.06 (1.03. 1.09)	1.11 (1.06, 1.16)
Mother Born in outside Canada	0.92 (0.31, 2.74)	0.65 (0.44. 0.98)	1.49 (0.76, 2.92)
Maternal Ethnicity non-European	2.14 (0.73, 6.27)	0.77 (0.51, 1.16)	0.70 (0.35, 1.41)

[1] This multinomial regression used four categories of BMI as the outcome: <-2 "underweight"; ≥-2 to 1 "normal weight"; ≥ 1 to 2 "overweight"; ≥ 2 "obesity". The reference group was the "normal weight" category. [2]RRR: Relative Risk Ratio; [3]95% CI: 95% Confidence Interval

Supplementary Table 2: Association between Income and Strengths and Difficulties Questionnaire (SDQ) Total Difficulties Score

	SDQ Quartile 2[1]	SDQ Quartile 3[1]	SDQ Quartile 4
Unadjusted	RRR[2] (95% CI[3])	RRR (95% CI)	RRR (95% CI)
Income <$80,000	0.63 (0.33, 1.22)	1.69 (0.94, 3.03)	1.88 (1.06, 3.33)
Adjusted	RRR (95% CI)	RRR (95% CI)	RRR (95% CI)
Income <$80,000	0.49 (0.23, 1.03)	1.46 (0.73, 2.89)	1.35 (0.68, 2.65)
Child			
Age (months)	0.99 (0.97, 1.01)	0.98 (0.97, 1.00)	0.99 (0.97, 1.00)
Sex (male)	1.09 (0.71, 1.66)	1.15 (0.73, 1.81)	1.53 (0.97, 2.40)
Birthweight (kg)	0.95 (0.66, 1.37)	1.06 (0.72, 1.57)	0.98 (0.66. 1.44)
Living Arrangement	2.84 (0.73, 11.11)	3.26 (0.83, 12.86)	3.84 (1.01, 14.66)
Parent			
Maternal Age at Birth	0.97 (0.92, 1.02)	0.97 (0.91, 1.02)	0.95 (0.90, 1.01)
Maternal Education	0.53 (0.28, 0.99)	0.79 (0.40, 1.54)	0.63 (0.33, 1.20)
Mother Born in outside Canada	0.85 (0.50, 1.46)	0.83 (0.78, 1.47)	0.91 (0.52, 1.59)
Maternal Ethnicity non-European	0.96 (0.58, 1.59)	1.18 (0.70, 2.00)	1.09 (0.64, 1.86)

[1] This multinomial regression used four quartiles of SDQ Total Difficulties Score as outcome, with the first quartile as reference.
[2]RRR: Relative Risk Ratio; [3]95% CI: 95% Confidence Interval

Supplementary Table 3: Association between Income and Total Infant Toddler Checklist (ITC) Score

	ITC Quartile 2[1]	ITC Quartile 3[1]	ITC Quartile 4[1]
Unadjusted	RRR[2] (95% CI[3])	RRR (95% CI)	RRR (95% CI)
Income <$80,000	0.82 (0.55, 1.22)	0.46 (0.28, 0.74)	0.35 (0.21, 0.57)
Adjusted	RRR (95% CI)	RRR (95% CI)	RRR (95% CI)
Income <$80,000	1.13 (0.69, 1.84)	0.53 (0.30, 0.95)	0.44 (0.25, 0.80)
Child			
Age (months)	1.29 (1.05, 1.59)	1.25 (1.00, 1.57)	1.56 (1.27, 1.93)
Sex (male)	0.55 (0.38, 0.78)	0.64 (0.43, 0.94)	0.45 (0.30, 0.66)
Birthweight (kg)	1.56 (1.14, 2.13)	1.39 (0.98, 1.95)	1.67 (1.20, 2.33)
Preterm	0.96 (0.54, 1.69)	1.54 (080, 2.97)	2.14 (1.06, 4.31)
Living Arrangement	0.93 (0.53, 1.61)	0.48 (0.19, 1.21)	1.17 (0.65, 2.10)
Parent			
Maternal Age at Birth	0.94 (0.90, 0.98)	0.90 (0.86, 0.95)	0.95 (0.91, 0.99)
Maternal Education	2.01 (1.19, 3.38)	1.48 (0.84, 2.61)	1.42 (0.82, 2.46)
Mother Born in outside Canada	0.91 (0.62, 1.33)	0.81 (0.54, 1.22)	0.84 (0.57, 1.26)
Maternal Ethnicity non-European	0.67 (0.44, 1.00)	0.77 (0.50, 1.19)	0.57 (0.36, 0.88)

[1] This multinomial regression used four quartiles of Total ITC Score as outcome, with the first quartile as reference. [2]RRR: Relative Risk Ratio; [3]95% CI: 95% Confidence Interval

STROBE Statement—Checklist of items that should be included in reports of ***cross-sectional studies***

	Item No	Recommendation	Page No
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	3
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	3-4
Objectives	3	State specific objectives, including any prespecified hypotheses	4
Methods			
Study design	4	Present key elements of study design early in the paper	5
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	5
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants	5
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	5-7
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	5-7
Bias	9	Describe any efforts to address potential sources of bias	7-8
Study size	10	Explain how the study size was arrived at	8
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	7-8
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	7-8
		(*b*) Describe any methods used to examine subgroups and interactions	7-8
		(*c*) Explain how missing data were addressed	7-8
		(*d*) If applicable, describe analytical methods taking account of sampling strategy	
		(*e*) Describe any sensitivity analyses	8
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	8, Figure 1
		(b) Give reasons for non-participation at each stage	N/A
		(c) Consider use of a flow diagram	Figure 1
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	9, Table 1
		(b) Indicate number of participants with missing data for each variable of interest	
Outcome data	15*	Report numbers of outcome events or summary measures	Table 1

Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	N/A
		(*b*) Report category boundaries when continuous variables were categorized	N/A
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	N/A
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	
Discussion			
Key results	18	Summarise key results with reference to study objectives	11
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	13-14
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	14
Generalisability	21	Discuss the generalisability (external validity) of the study results	14
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	1

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

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Understanding income-related differences in distribution of child growth, behaviour and development using a cross-sectional sample of a clinical cohort study

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Abbreviations:
BMI: Body mass index
SDQ: Strengths and Difficulties Questionnaire
ITC: Infant-toddler checklist

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Anne E Fuller conceptualized and designed the study, conducted the initial analyses, and drafted the initial manuscript, and reviewed and revised the final manuscript.
Arjumand Siddiqi conceptualized and designed the study, reviewed the analyses, and reviewed and revised the final manuscript.
Faraz V Shahidi and Vincent Hildebrand assisted with analysis, reviewed analyses, and reviewed and revised the final manuscript.
Laura N Anderson conceptualized and designed the study and reviewed and revised the final manuscript.
Charles Keown-Stoneman managed study data, assisted with analysis, and reviewed and revised the final manuscript.
Jonathon L Maguire conceptualized and designed the study and reviewed and revised the final manuscript.
Catherine S Birken conceptualized and designed the study, reviewed analyses, and reviewed and revised initial manuscript drafts and the final manuscript.
All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

ABSTRACT

Objectives: Children from low-income households are at an increased risk of social, behavioral, and physical health problems. Prior studies have generally relied on dichotomous outcome measures. However, inequities may exist along the range of outcome distribution. Our objective was to examine differences in distribution of three child health outcomes by income categories (high versus low): body mass index (BMI), behavior difficulties, and development.

Design and Setting: This was a cross-sectional study using data from a primary-care based research network with sites in three Canadian cities, and 15 practices enrolling participants.

Participants, Independent variable and Outcomes: The independent variable was annual household income, dichotomized at the median income for Toronto (< $80,000 or ≥$80,000 CAD). Outcomes were: 1) growth (BMI z-score (zBMI) at 5 years, 1628 participants); 2) behavior (Strengths and Difficulties Questionnaire (SDQ) at 3-5 years, 649 participants); 3) development (Infant Toddler Checklist (ITC) at 18 months, 1405 participants). We used distributional decomposition to compare distributions of these outcomes for each income group, and then to construct a counterfactual distribution that describes the hypothetical distribution of the low-income group with the predictor profile of the higher-income group.

Results: We included data from 1628 (zBMI), 649 (SDQ) and 1405 (ITC) children. Children with lower family income had a higher risk distribution for all outcomes. For all outcomes, thecounterfactual distribution, which represented the distribution of children with lower-income who were assigned the predictor profile of the higher income group, was more favorable than their observed distributions.

Conclusion: Comparing the distributions of child health outcomes and understanding different risk profiles for children from higher and lower income groups can offer a deeper understanding of inequities in child health outcomes. These methods may offer an approach that can be implemented in larger datasets to inform future interventions.

Strengths and limitations of this study

Strengths of this study include:

- Large sample of young children in a major urban area in Canada
- Use of distributional decomposition offers a novel alternative to simple regression for this population and these outcomes
- All outcomes defined using objective measures or validated instruments relevant to clinical practice

Limitations of this study include:

- Limits to generalizability related to lower proportion of children from lower income households and recruitment from primary care practices in an urban setting
- Important predictors for each outcome may not have been included in this analysis

INTRODUCTION

Income is an important determinant of child health, with children living in households from the lowest income quintile experiencing poorer health outcomes on multiple measures.[1] Lower socioeconomic status, the broader construct that speaks to the material and social resources of families that are linked to income and education, has been associated with poorer child health outcomes across domains[2], including increased risk learning disability or serious behavioral difficulty, poorer educational outcomes[3], and mental health challenges.[4]

There is a strong argument in favour of using continuous outcome measures in population health research. While population-level means or categorical definitions of outcomes may show improvement in important health outcomes over time, inequities may be overlooked by not examining the distributions of outcomes.[5] Research findings based on categorized outcomes may be easier to use in clinical practice. However, studying continuous measures can reduce bias that may be introduced with assigning categories and may increase statistical power.[6] Observing differences across the entire distribution may have important health implications but may not be captured in collapsed categories or using standard statistical tests due to smaller sample sizes at the tails of distributions or small but cumulatively important effect sizes. Understanding inequities in the full range of outcome distribution may also provide more nuanced findings to inform specific interventions.[7, 8]

As research in the health sciences strives to generate evidence to support reducing inequities in child health, understanding inequities across the full range of outcome distribution

may yield important knowledge that could inform specific targeted or population-level interventions, but may be overlooked using standard methods. However, research examining distributions in child health is extremely scarce. A scoping review exploring the literature assessing birth weight identified a conceptual rationale for studying inequities in distributions, but a gap in the use of distributions analytically in favour of categorical analyses such as quantile regression.[9] Distributional decomposition is a method which has been used to explore inequities in distribution of outcomes in studies of health outcomes in adults, including body mass and blood pressure.[7, 10] This method offers an opportunity to observe differences between groups across the entire distribution of health outcomes, and then, by producing a counterfactual distribution of the outcomes by applying predictor profiles of one group to the other, to explore the ways in which possible predictors of the outcome may account for differences observed.

Obesity, mental illness and developmental delays are among the most significant chronic conditions faced by children and they share risk and protective factors,[11, 12] including poverty and childhood adversity.[13] However, there is limited research examining income inequities in very young children, and data from population-based clinical cohorts is scarce. Our first objective was to examine differences in the distribution of three child health outcomes in young children by income: body mass index (BMI), behavior difficulties, and development. Our second objective was to demonstrate a method called distribution decomposition which can be used to explore the extent to which differences between income groups across the outcome distribution can be accounted for by common predictors for each outcome.

METHODS

Study Design, Setting and Participants

This was a cross-sectional study of children enrolled in the TARGet Kids! Research Network. TARGet Kids! is a primary care practice-based research network in the Greater Toronto Area and Kingston, Ontario, and Montreal, Quebec. Children less than 6 years old are recruited by trained research personnel embedded at primary care paediatric and family medicine practices. They are followed prospectively into adolescence. Participants complete standardized questionnaires and have anthropometrics measured at scheduled healthcare maintenance visits and are followed yearly. The sample used for this analysis includes outcomes collected from 2008-2019. The study protocol and sample population have been described in detail.[14]

Exclusion criteria at enrollment are health conditions affecting growth, severe developmental delay, chronic health conditions (except asthma and high functioning autism), birth less than 32 weeks' gestation and families unable to complete questionnaires in English. This study was approved by the Research Ethics Board at the Hospital for Sick Children (REB # 1000012436), Unity Health Toronto, and McGill University.

Patient and Public Involvement

The TARGet Kids! Research Network includes a Parent and Clinician Team (PACT) which is actively involved in guiding the research directions and priorities of TARGet Kids!.[15]Parents and patients were not actively involved in the design of this secondary analysis of existing TARGet kids! data. Results are disseminated to study participants through study communications and the TARGet Kids! website.

Study Assessments

Independent Variable

The independent variable was parent-reported annual household income. It is collected in the standardized TARGet Kids nutrition and health questionnaire with a single question, "what

was your family income before taxes last year," with 13 response categories, ranging from "less than $10,000" to "greater than $500,000." We created two categories, dichotomized at approximately the median household income in the Toronto Census Metropolitan Area based on the 2016 Canadian census (< $80,000 or ≥$80,000 CAD).We dichotomized at the median income.[16] We selected this cut point to represent a common measure of household income, and to ensure a robust sample size in both groups to permit the analysis.

Dependent Variables

Dependent variables were: 1) growth (body mass index z-score (zBMI) at 5 years); 2) child behavior (total difficulties score on the Strengths and Difficulties Questionnaire (SDQ) at 3-5 years); 3) development (total score on the Infant Toddler Checklist (ITC) at 18 months).

To assess zBMI, height and weight were measured by trained research assistants according to standard protocols.[17] BMI was calculated as weight in kilograms divided by squared heighted in meters and measured at 5 years old. Age and sex standardized zBMI was calculated using the recommended WHO growth standards.[18]

To assess child behavior, we used the Strengths and Difficulties Questionnaire (SDQ) total difficulties score, measured between 3 and 5 years of age. The SDQ has been validated in children of all ages and across multiple countries and cultural groups.[19, 20] The score is comprised of 20 questions, and measures emotional problems, conduct problems, hyperactivity, and peer problems. Higher score indicates greater difficulties.

To assess child development, we used the Infant Toddler Checklist (ITC – also known as the Communication and Symbolic Behavior Scales: Developmental Profile), measured between 18 and 24 months.[21, 22] This is a measure for clinical screening of social and communication

developmental risk, validated for use between 6 and 24 months. Lower score indicates greater developmental risk.

Covariates

Child and maternal characteristics were used to produce predictor profiles. We selected these predictors to represent confounders commonly included in adjusted regression models and other analyses within the literature more broadly. For children, these were age (months), sex, birthweight (kilograms), and living arrangement (living with both parents, or any other arrangement) for all models; gestational age (32 to 36 weeks, 37 weeks and greater) was included for ITC models only as an important predictor of development.[23], and total months breastfed. For mothers, these were maternal age (years), education (high school or less, university or more), immigration status (born in Canada, born outside of Canada), ethnic ancestry (European/White, other) and body mass index (kg/m^2). Breastfeeding duration, and maternal BMI were included in the BMI models only as important predictors of child BMI.[24]

Statistical Analysis

We used descriptive statistics to characterize the study population and describe the means and proportions of the outcomes of interest. We used Mann-Whitney and chi-square tests to compare predictors by income category. We used Kolmogorov-Smirnov tests to assess differences between distribution curves for each outcome. Using methods described by Siddiqi et al[7], who adapted the DiNardo-Fortin-Lemieux decomposition[25], we then measured the *distributional inequality.* We first estimated the probability densities of each outcome for each income subgroup using an adaptative kernel estimator. We then calculated d*istributional inequality* as the difference between the kernel density estimates of the two income subgroups. At any given point, it measures the difference between proportion of children in the lower-

income group and those in the higher income group. We depicted the kernel density distributions and the distributional inequality graphically.

We then proceeded with *distributional decomposition* separately for each outcome. Distributional decomposition offers a method to identify the proportion of inequality at each point in the outcome distribution that can be explained by a set of common predictors using a simple reweighting method originally developed by DiNardo et al.[25] The syntax for this specific analysis using Stata was developed and refined by members of our team (V. Hildebrand). We estimated the counterfactual density function for each outcome of the lower-income group that would prevail were children in the lower-income group given the predictors of the higher income group. This involves reweighting the density function of the lower-income group such that the reweighted sample of children in the lower-income group has the same predictors of the children in the higher income group.[7, 25] We then used the counterfactual weight to reweight the kernel density estimates to produce the counterfactual distribution. This counterfactual density distribution demonstrates how the observed distribution of the children in the lower-income group would change if they took on the predictor profile of children in the higher-income group. We plotted this re-weighted counterfactual distribution to compare it visually to the original distributions for the higher- and lower-income groups.

Because of smaller numbers of children at the high and low ends of the distributions of each variable for the lower-income group, we undertook a sensitivity analysis, reversing the re-weighting by applying the predictor profile of the lower-income group to the higher-income group. This increases the likelihood of achieving "common support", where all configurations of predictor profiles of the re-weighted group are present in the reference group. We would expect the distribution to appear like the inverse of the first one.

As an additional analysis, to examine associations between income and each outcome, we also performed unadjusted and adjusted multinomial regression analyses. For zBMI, we used a four-category outcome based on clinical risk stratification and defined the variable as BMI z-score less than -2, greater than or equal to -2 to 1, greater than or equal to 1 to 2, and greater than or equal to 2. For zBMI, the reference group was set as the second category (normal weight status). For SDQ and ITC scores, we divided the total score into quartiles. For these outcomes, the reference group was set to the first quartile.

Statistical analyses were performed using Stata (v 14.2, College Station, Texas).[26]

RESULTS

For the BMI outcome 2,123 children between 60 and 71 months had complete outcome and income reported, of whom 1,628 (76 % of total) had complete information for all variables and were included. For our SDQ cohort, 774 had complete outcome and income reported, 649 (84% of total) of whom had complete information for each variable and were included. For our ITC cohort, 1698 had complete outcome and income reported, 1405 (81% of total) of whom had complete information for each variable and were included (Figure 1).

The predictor profiles of children from higher and lower-income households are shown in Table 1. Children from lower-income households had a shorter duration of breastfeeding, had mothers who were younger; a lower proportion lived with both parents, had fewer mothers with a university education; a greater proportion had mothers who were immigrants to Canada or reported ethnic ancestry as other than European.

Body Mass Index

A greater proportion of children with higher income were in the normal weight category compared with children with lower-income (84.9% vs 77.4%), while a greater proportion of

children with low income were in the underweight, overweight, and obesity categories (Table 1). KST test showed evidence of statistically significant difference between distributions income groups (p=0.004). Comparing the density distributions by income category, the distribution of children with high income was more concentrated around a zBMI of zero, while a higher proportion of children with low-income were at the tails of the distribution (Figure 2a). Figure 2b shows the difference between the observed distributions.

When children from lower-income households were re-weighted to have the predictor profiles of children from higher-income households, the distribution of zBMI within the normal range (-1 to 1) narrowed. This re-weighted distribution is shown with the observed distributions in Figure 2c. The residual, unexplained difference between the re-weighted distribution and the higher-income distribution is shown in Figure 2d. In this normal range, the difference between the re-weighted distribution for children from lower-income households and the distribution of children from higher-income households decreased substantially (Figure 2d). However, at the tails of the distribution, the re-weighted distribution curve was largely unchanged from the observed distribution.

Strengths and Difficulties Questionnaire

Children from higher-income households had a lower mean SDQ score (7.2 vs 9.0) (table 1). KST test showed evidence of statistically significant difference between distributions income groups (p=0.002). Comparing the density distributions by income category, the differences in distribution were most notable in the lower and middle range of the score distribution, which had a lower proportion of children from lower-income households (Figure 3a). There was a greater proportion of children from lower-income households in the high- risk range (>17) as well. Figure 3b shows the difference between the observed distributions.

The re-weighted distribution of SDQ total difficulties score for children from lower-income families in the low-risk range shifted to the left, with a greater proportion having even *lower scores* than before. This re-weighted distribution is shown with the observed distributions in Figure 3c. The residual distribution had two peaks in the low-risk range, which were higher than the observed distribution for children from higher-income households, and a third peak in the high-risk range. The residual, unexplained difference between the re-weighted distribution and the high-income distribution is shown in Figure 3d.

Infant-Toddler Checklist

Children from higher-income households had a higher mean ITC score indicating lower risk (46.6 vs 44.5) (table 1). KST test showed evidence of statistically significant difference between distributions income groups ($p<0.001$). Comparing density distribution by income, the differences were notable across the distribution, with a greater proportion of children from lower-income households in the higher risk range (Figure 4a). Figure 4b shows the difference between the observed distributions.

The re-weighted distribution of ITC score for children from lower-income households shows that the distribution in the low-risk range (higher scores) is like the observed distribution from high income households, indicating that common predictors explain much of the difference. This re-weighted distribution is shown with the observed distributions in Figure 4c. However, as total ITC score decreases into higher risk ranges, the re-weighted distribution still shows a greater proportion of children from low-income households with lower scores. The residual, unexplained difference between the re-weighted distribution and the high-income distribution is shown in Figure 4d.

Sensitivity Analyses

Our sensitivity analysis, presented in supplement 1, which re-weighted the predictor profiles of children from higher-income households to have the predictor profile of children from lower-income households, showed a generally similar pattern in the low-risk range of the distribution for each outcome. Most notably, for SDQ, this analysis resolves the second peak of unexplained difference in the high-risk range, suggesting this may be due to low sample size in the lower-income group at the high end of the distribution.

Multinomial regression models for each outcome are found in supplement 2. The models generally demonstrate that lower income is associated with higher zBMI, higher SDQ Total Difficulties Score score, and lower ITC score. There was evidence of confounding by the covariates included.

DISCUSSION

In this study with a large cohort of young children, we found that there were notable differences in the distributions of children from higher and lower-income households for three important outcomes studied: zBMI, total behavioral difficulties, and developmental risk, with a greater proportion of children with higher-income in the low-risk range of the distribution, and a greater proportion of those with lower-income in the higher risk range. When the distributions for children with lower-income were re-weighted to give them the predictor profiles of children with higher-income children, children with lower-income already in the low-risk range adopted a distribution that appeared to be *even lower risk.* After re-weighting, children in the lower-income group with behavioral and developmental outcomes in the high-risk range adopted a distribution with a lower proportion of children at high risk. This was not the case for zBMI, where the re-weighted distributions were like the observed distributions. Comparing observed

distributions, the difference between income categories in the higher risk ranges (obesity, underweight) are smaller than the differences in the lower risk range (normal weight).

By comparing the observed distributions of continuous measures of child health by income, we can appreciate inequalities that may not be captured using categorical definitions that are used for clinical risk stratification. Categorical measurement can collapse variation within each category, and this variation can yield important information. These inequalities may have clinical meaning; for example, small differences in SDQ score or in zBMI are related to differences in long-term behavior and cardiometabolic outcomes, respectively.[27, 28] Small differences in risk early in life may continue to grow through the life-course. For example, higher BMI in early life is associated with greater risk of obesity later.[29] While the multinomial regression analyses generally support the differences observed in distributions, visualizing the distributions offers a clearer picture of differences in the distribution, including transition points, for example, when distribution curves cross. Comparing distributions offers the opportunity to disaggregate differences that may not be appreciated with categorical outcome definitions.

The distributional decomposition analysis adds a further layer to our understanding of potential explanations for these inequities. For all outcomes, we found that the inequality between the observed distribution of children with higher-income and the counterfactual distribution was lower than the inequality between observed distributions of children within the "low-risk" range of the distribution. However, in the higher risk range, the counterfactual reduced the inequality to a variable degree depending on outcome. We suspect that the determinants of having clinically meaningful concerns about growth, behavior or development are different than the determinants of where an individual falls in the lower risk range. For example, clinically significant behavior difficulties on the SDQ may represent an underlying

behavior disorder such as attention-deficit disorder, while within the low-risk range, other factors such as parenting behaviors, which are more closely related to predictors in our predictor profiles, may be more influential.

For zBMI, the counterfactual distribution demonstrates that routine predictors of BMI explain some of the income-related inequality in the distribution within the normal range but does not explain the inequalities observed for children with obesity and underweight. It is possible that the determinants of obesity could be different than the determinants of underweight[30], or that low income is a primary driver of BMI.[31, 32]

Compared to zBMI, routine predictors of child behavior and mental health can explain more of the income-related inequality in the distribution of SDQ score, including at the higher range of the distribution. The highest risk range of the distribution may have represented children with significant morbidity, which likely has different predictors than a lower score. Our sensitivity analysis, which re-weighted the children with high-income to have predictors of children with low-income, resolved this issue, suggesting sample size in the distribution of predictors for the lower-income group may be a contributor. The counterfactual distribution of the ITC was the closest to the observed distribution of children with higher-income of the three child health outcomes studied. It is possible that ITC had the strongest income-related predictors of the outcome included in the model, with parental education as a particularly important driver of parent-toddler communication, promoting language development.[33]

This study has several strengths. It includes a large sample of young children in a major urban area in Canada and employs a novel and revealing analysis. All outcomes were defined using objective measures (zBMI) orvalidated instruments (SDQ and ITC), which are relevant to clinical practice. This study also has certain limitations. Our sample had a lower proportion of

children in the lower-income group, and particularly at the tail ends of distributions where there were fewer children overall, fewer children with each covariate pattern may have led to reduced robustness of the re-weighted counterfactual. Future research could explore alterative categories of income. There was a smaller proportion of participants with certain characteristics which required categorization of certain predictors and did not allow for stratification by potentially important predictors (eg. race/ethnicity). Children with missing data may come from households with low-income or other stressors and are not represented. Furthermore, as our sample was drawn from a clinical setting, our recruitment and data collection process may have led to selection bias, with children from low-income families with poorer health over-represented compared to those with better health. This study is cross-sectional and causality cannot be inferred. Importantly, the relationship between income and health is likely bi-directional; while low-income may lead to poorer health outcomes, there is also evidence to suggest that chronic illness in childhood has adverse impacts on family income.[34] One further consideration is the possibility that predictors of each outcome are also predictors of income (such as maternal education). In this case, some of the effects of income may actually be caused by these predictors. It is also likely that there are other meaningful predictors of each outcome that were not included in our predictor profile and may be important to the relationship between income and each outcome. For example, variables such as number of children in household, parenting styles and diet quality could be related to both income and outcome. Future research could explore a more detailed conceptual model of income-related predictors of each outcome to shed light on additional variables and incorporate longitudinal data to better understand causal relationships. Finally, the study takes place in primary care practices in a major urban area in Canada, participating families had higher income, were English-speaking, and may not be

representative of children who lack access to primary care, live in rural areas, or who have other barriers to participation in a longitudinal study. Future research should seek out populations of children who are under-represented in these analyses.

CONCLUSIONS

This study examining income-related differences in child growth, behavior, and development found that there were differences in the distribution of each outcome between children from higher and lower-income families, with children from lower-income families showing a higher risk profile. Common predictors of each outcome partially explained the inequality, most notably in the low-risk range. These findings have important implications for health policies and interventions targeting income-based health inequities. Identifying that inequities likely have different predictors across the distribution suggests that future research should further explore predictor profiles that can explain income-related inequities in child health outcomes with a broader scope. It is possible that interventions to reduce inequities by addressing common predictors may improve outcomes in the low-risk range. However, targeted interventions addressing income specifically, as well as the circumstances experienced by families with low-income, may be for those at high risk.

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Figure Captions

Figure 1: These flow diagrams show cohort definitions for each outcome and reasons for participant exclusion due to missing data.

Figure 2:

Distributions and distributional decomposition of BMI z-score, including observed distributions of BMI z-score by income (2a); differences between observed distributions (2b); observed distribution plus the counterfactual distribution of the low-income group with predictor profile of high-income group (2c); and the residual difference between the high-income and counterfactual distributions (2d).

Figure 3:
Distributions and distributional decomposition of SDQ Total Difficulties Score, including observed distributions of Total Difficulties Score by income (3a); differences between observed distributions (3b); observed distribution plus the counterfactual distribution of the low-income group with predictor profile of high-income group (3c); and the residual difference between the high-income and counterfactual distributions (3d).
Figure 4:
Distributions and distributional decomposition of Total ITC Score, including observed distributions of ITC Score by income (4a); differences between observed distributions (4b); observed distribution plus the counterfactual distribution of the low-income group with predictor profile of high-income group (4c); and the residual difference between the high-income and counterfactual distributions (4d).

Ethics Statement:

This study was approved by the Research Ethics Board at the Hospital for Sick Children (REB # 1000012436), Unity Health Toronto, and McGill University.

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Table 1: Participant characteristics and outcomes by income category for each outcome cohort

Characteristic, n (%)	BMI[1] (n= 1,628)			SDQ[2] (n=649)			ITC[3] (n=1405)		
Predictors	Full Sample (n=1,628)	Income ≥ $80,000 (n=1,180)	Income < $80,000 (n=448)	Full Sample (n=649)	Income ≥ $80,000 (n=539)	Income < $80,000 (n=110)	Full Sample (n=1,405)	Income ≥ $80,000 (n=1,106)	Income < $80,000 (n=299)
Child									
Age (months) (mean, SD)	62.6 (2.8)	62.5 (2.7)	62.8 (3.0)	47.5 (12.3)	47.1 (12.3)	49.6 (12.2)	18.6 (0.98)	18.6 (0.97)	18.6 (1.0)
Sex									
Female	795 (48.8)	574 (48.6)	221 (49.3)	323 (49.7)	277 (51.4)	46 (41.8)	638 (45.3)	491 (48.5)	145 (48.5)
Male	833 (51.2)	606 (51.4)	227 (50.7)	326 (50.2)	262 (48.6)	64 (59.2)	614 (85.6)	615 (51.5)	154 (51.5)
Birthweight (kg) (mean, SD)	3.3 (0.6)	3.3 (0.6)	3.2 (0.7)	3.2 (0.6)	3.2 (0.6)	3.1 (0.6)	3.3 (0.7)	3.3 (0.7)	3.2 (0.7)
Gestational Age <37 weeks							189 (13.5)	147 (13.3)	42 (14.1)
Total Months Breastfed	12.6 (9.8)	12.9 (9.1)	12.0 (11.4)						
Lives with Both Parents	1,497 (92.0)	1,134 (96.1)	363 (81.0)	620 (95.5)	522 (96.8)	98 (88.7)	1,346 (95.8)	1,091 (97.7)	265 (88.3)
Parent									
Maternal Age at Birth (mean, SD)	33.3 (4.5)	33.9 (3.9)	31.6 (5.6)	33.6 (4.2)	34.0 (3.9)	31.7 (4.8)	33.9 (4.1)	34.4 (3.7)	32.2 (4.9)
Maternal Education									
University or more	1,491 (91.6)	1,138 (96.4)	353 (78.8)	534 (82.3)	476 (88.3)	58 (52.7)	1,154 (82.1)	993 (99.8)	161 (53.9)
High school or less	137 (8.4)	42 (3.6)	95 (21.2)	115 (17.7)	63 (11.7)	52 (47.3)	251 (17.9)	113 (10.2)	138 (46.2)
Maternal BMI	24.7 (4.9)	24.3 (4.5)	25.7 (65.8)						
Mother Born in Canada									
Yes	1,114 (68.4)	906 (76.8)	208 (46.4)	436 (67.2)	403 (74.8)	33 (30.0)	978 (69.6)	844 (76.3)	134 (44.8)
No	514 (31.6)	274 (23.2)	240 (453.6)	213 (32.8)	136 (25.2)	77 (70.0)	427 (30.4)	262 (23.7)	165 (55.2)
Maternal Ethnicity									
White/European	1,162 (71.4)	909 (77.0)	253 (56.5)	390 (60.1)	353 (65.5)	37 (33.6)	886 (63.6)	766 (69.3)	120 (40.1)
Other	466 (28.6)	271 (23.0)	195 (43.5)	259 (39.9)	186 (34.5)	73 (66.4)	519 (36.9)	340 (30.7)	179 (59.9)
Outcomes									
BMI z-score Category (n, %)									
< -2.0 (underweight)	25 (1.2)	17 (1.1)	8 (1.3)						
≥-2.0 – <1.0 (normal)	1,760 (82.3)	1276 (84.9)	471 (77.4)						
>1.0 – <2.0 (overweight)	273 (12.8)	175 (11.6)	96 (15.5)						
≥ 2.0 (obesity)	80 (3.7)	36 (2.4)	44 (7.1)						
SDQ Score (mean, SD)				7.5 (4.5)	7.2 (4.2)	9.0 (5.2)			
ITC Score (mean, SD)							46.6 (5.8)	47.4 (5.1)	44.5 (7.0)

[1] BMI: Body Mass Index; [2] SDQ: Strengths and Difficulties Questionnaire; [3] ITC: Infant Toddler Checklist

Figure 1: Defining the Cohorts

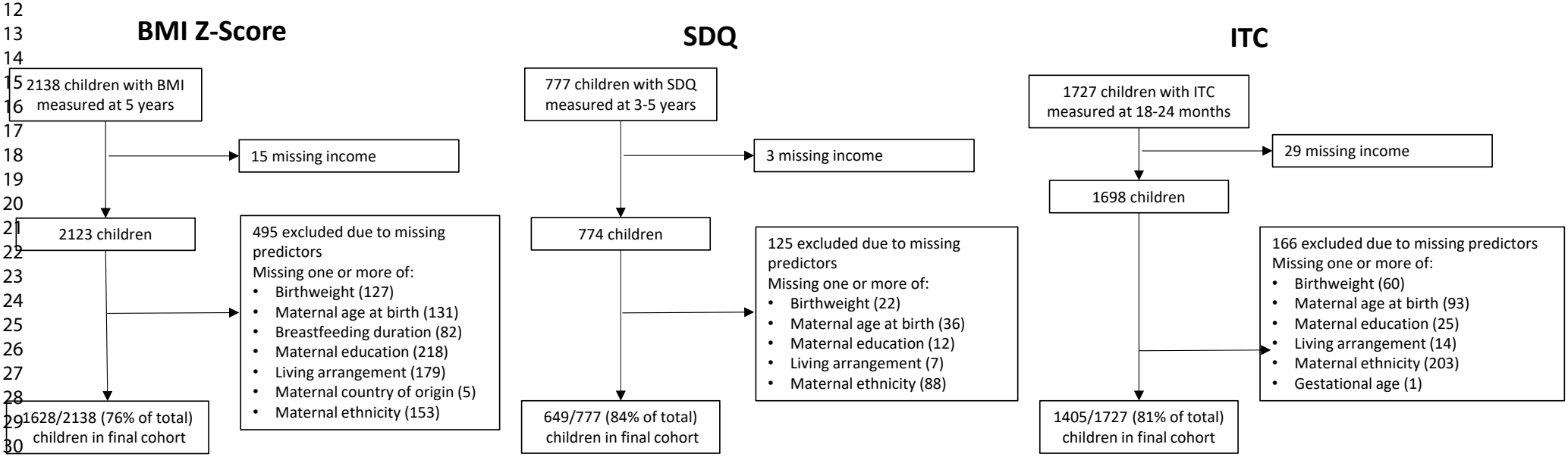
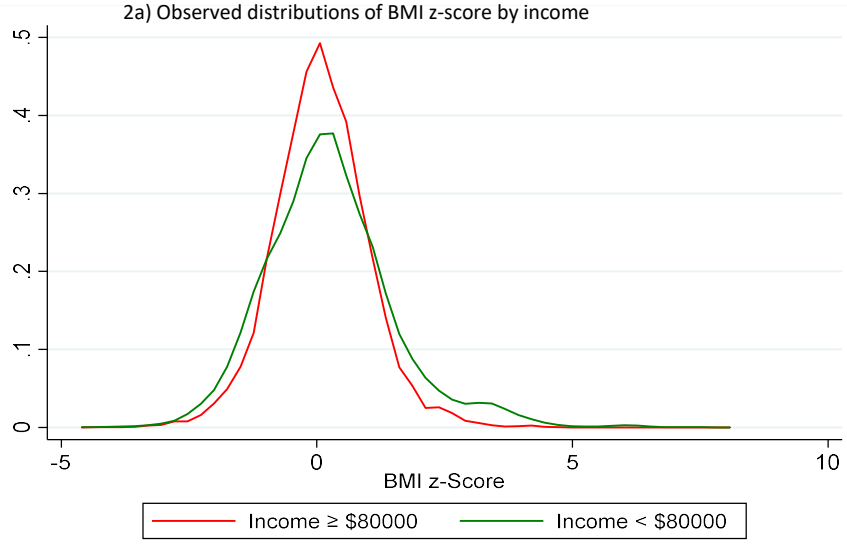
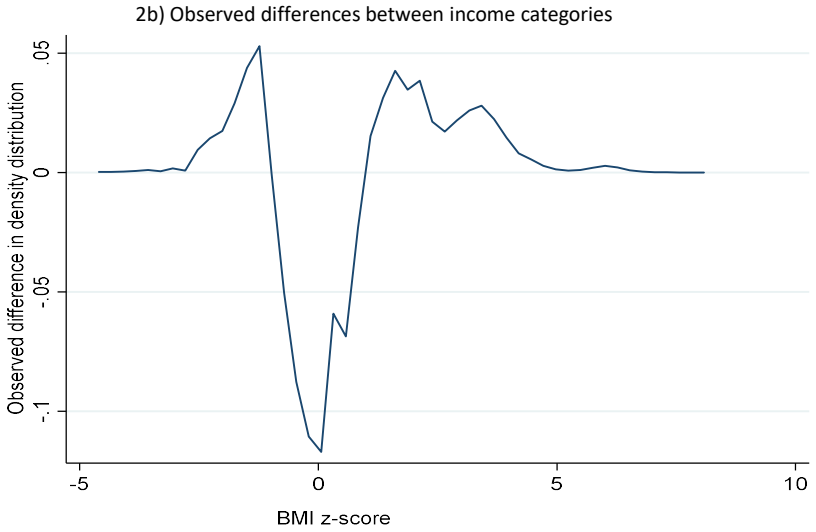
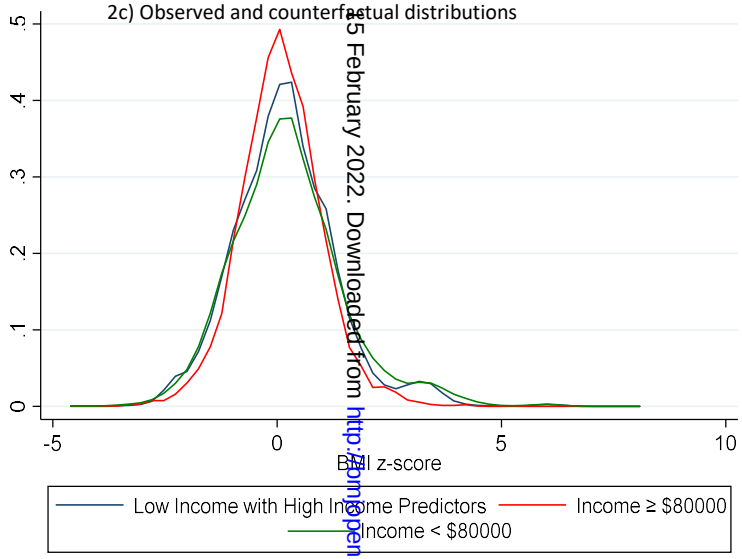


Figure 2: BMI z-score







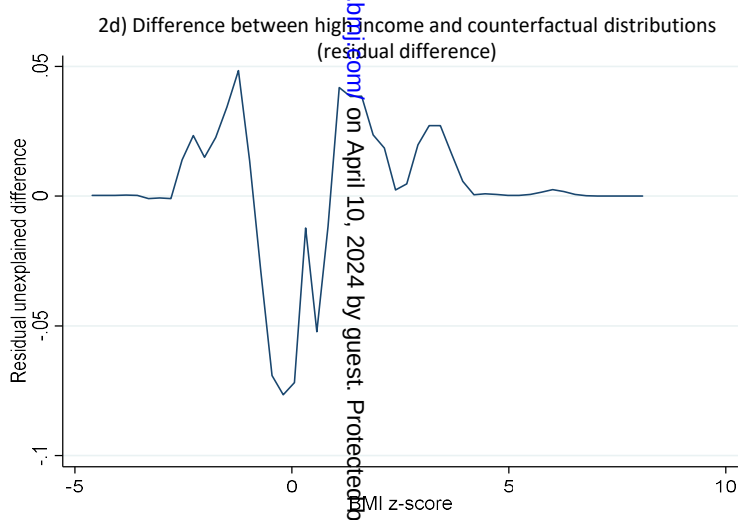


Figure 3: SDQ Total Difficulties Score

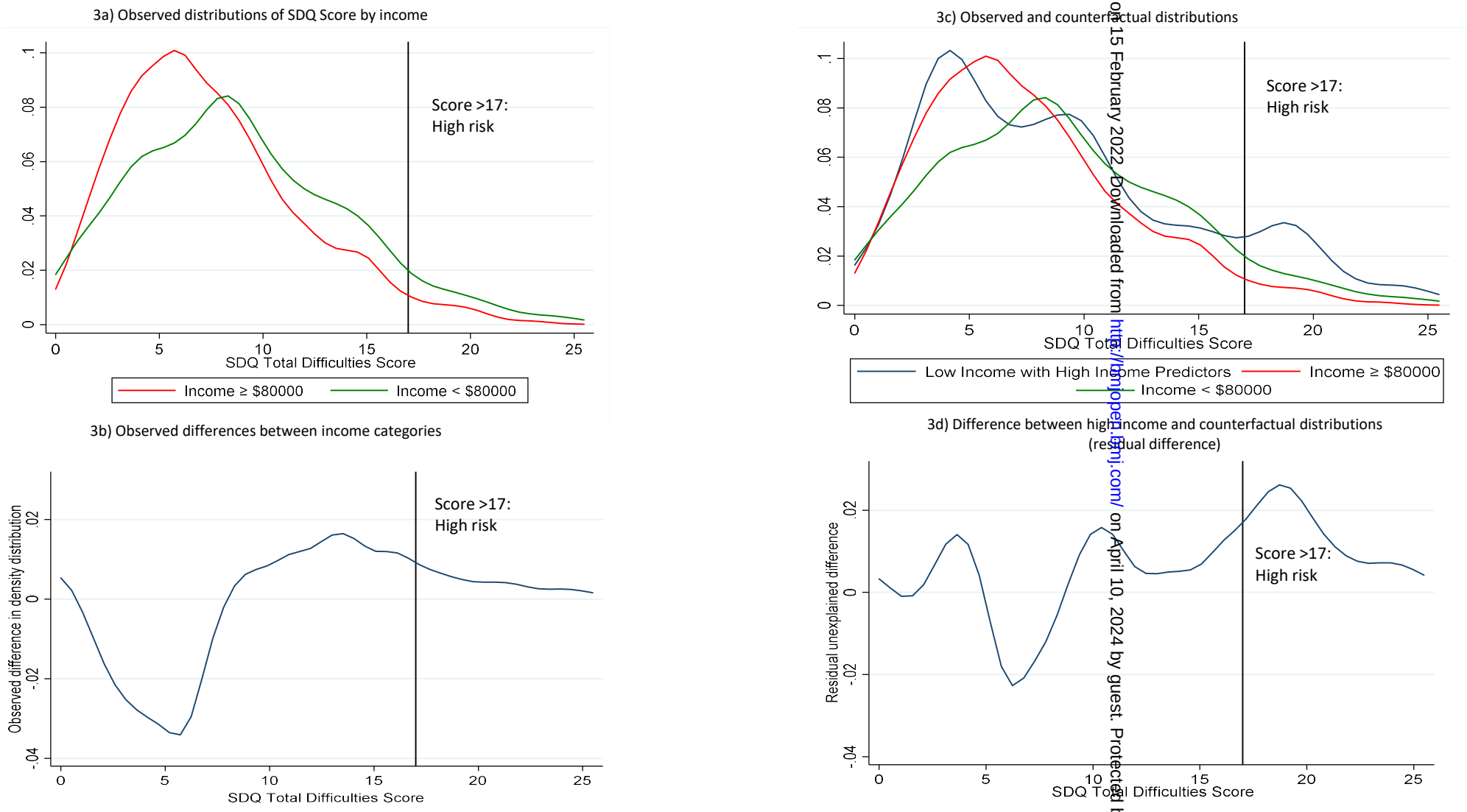
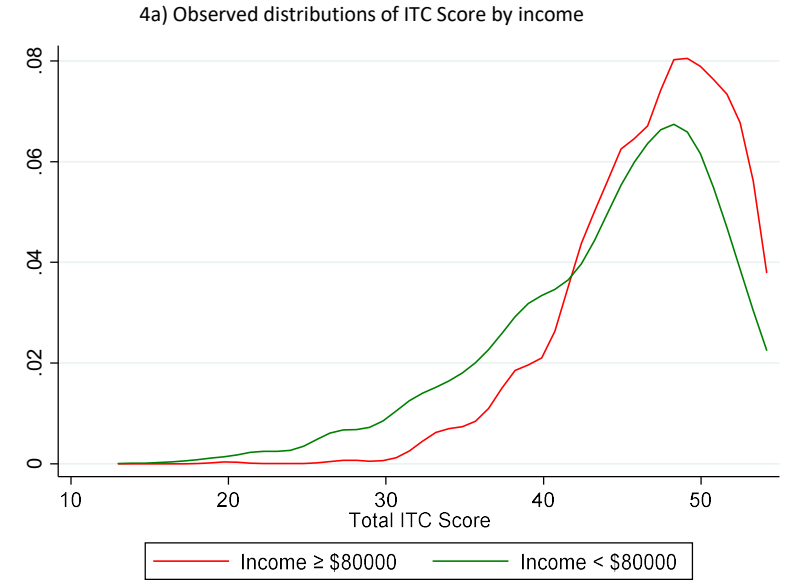
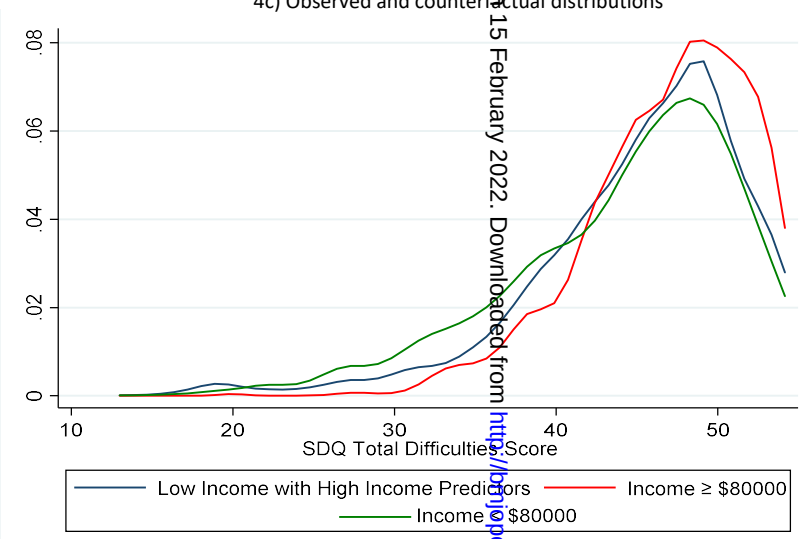
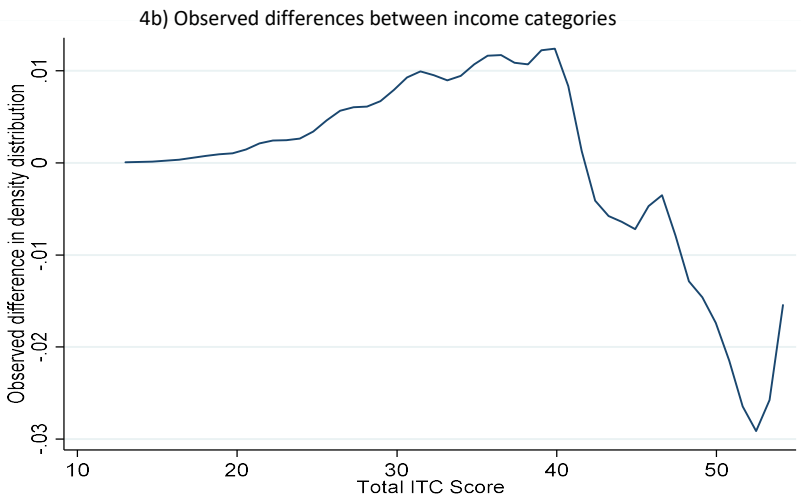


Figure 4: Total ITC Score







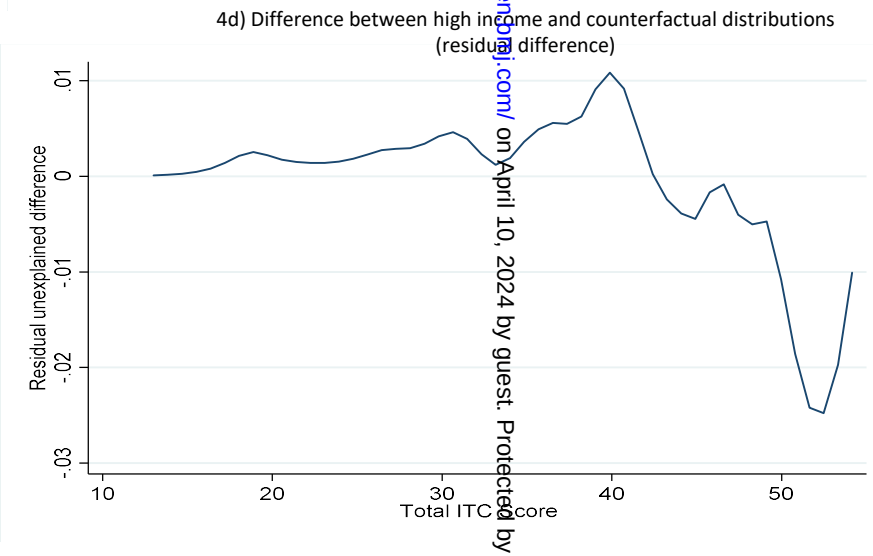
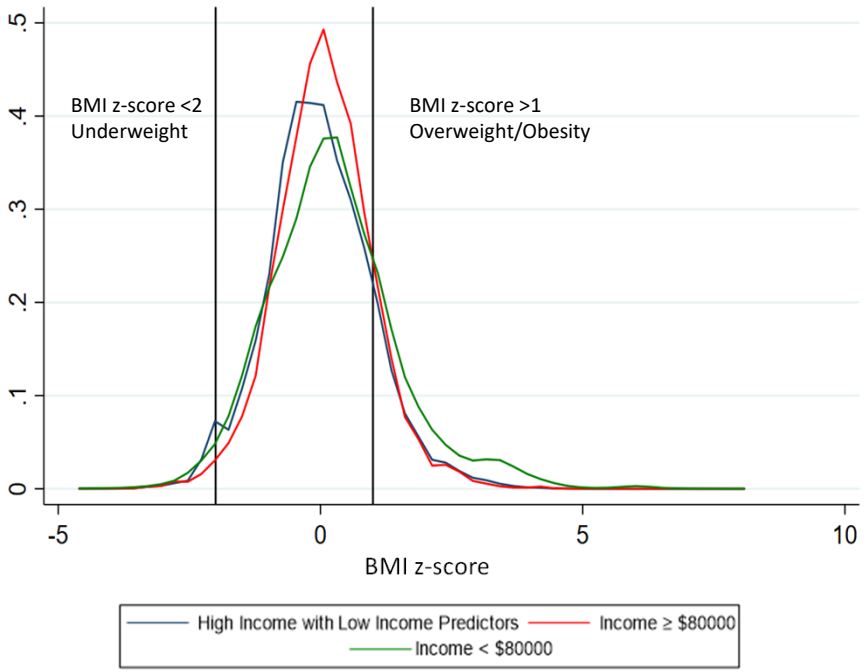
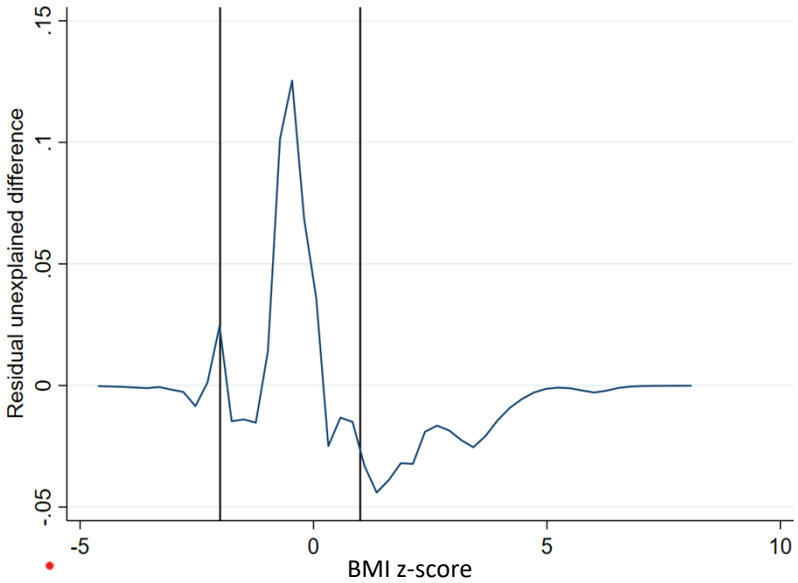


Figure 1: BMI Z-Score Distributional Decomposition

1a) Observed and counterfactual distributions



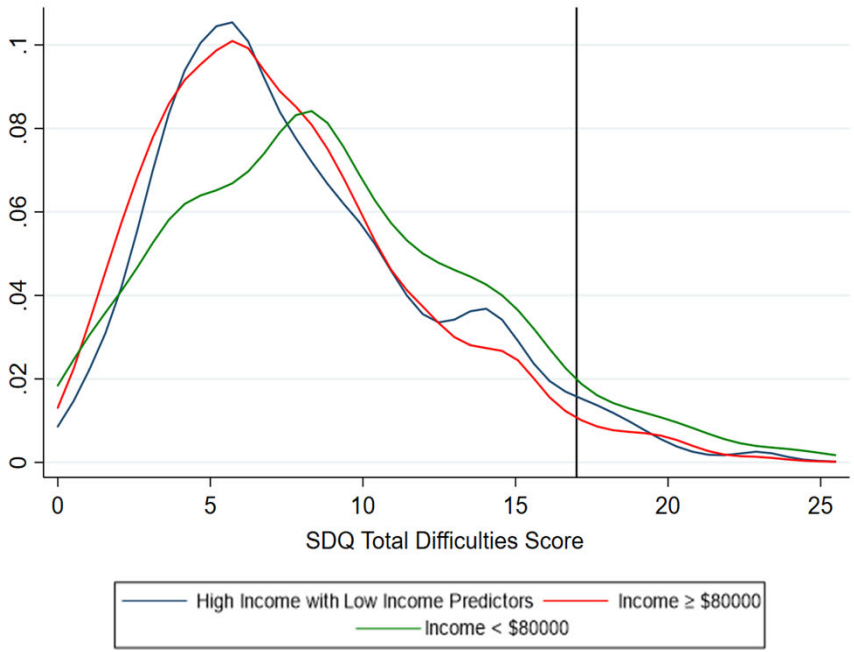
1b) Residual difference between lower income and counterfactual distributions



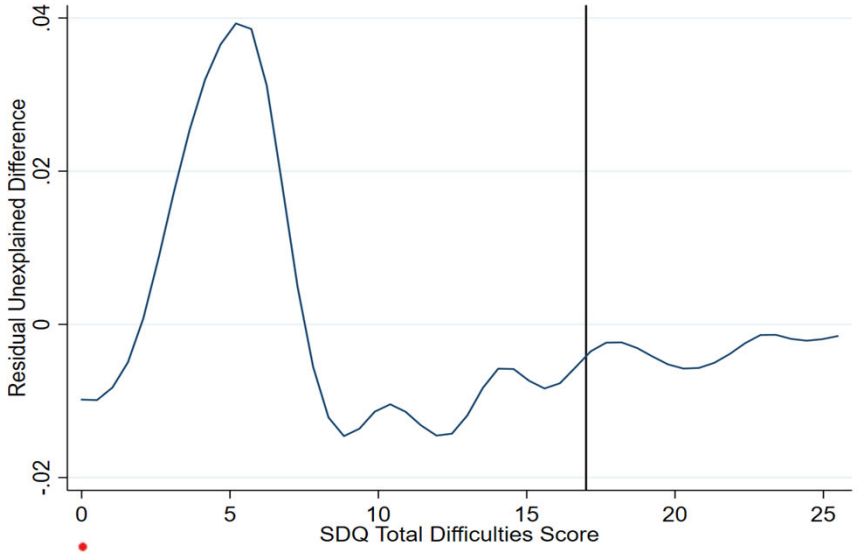
Higher income group re-weighted to have predictor profiles of lower-income group

Figure 2: SDQ Distributional Decomposition

2a) Observed and counterfactual distributions



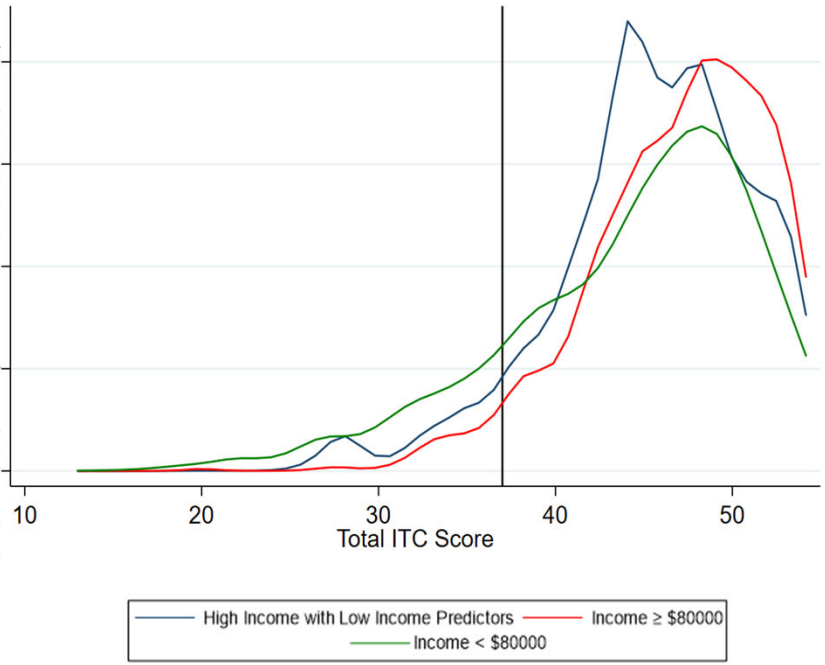
2b) Residual difference between lower income and counterfactual distributions



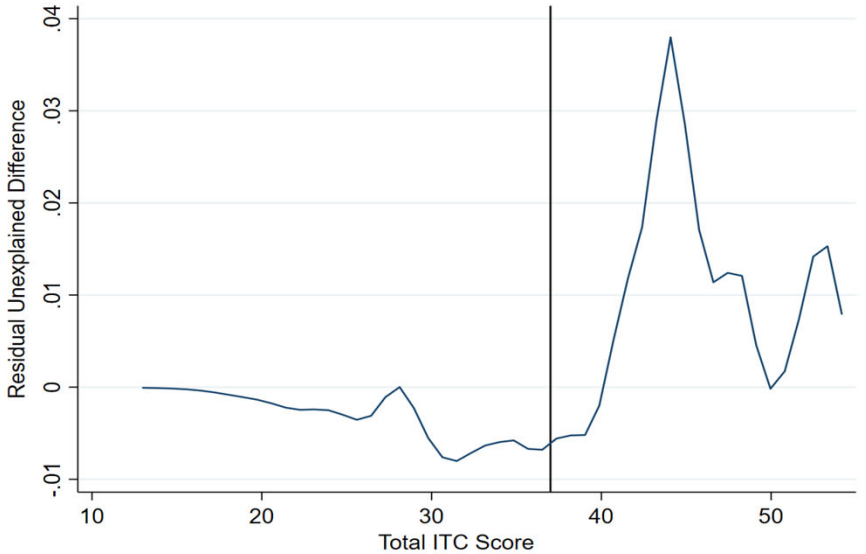
Higher income group re-weighted to have predictor profiles of lower-income group

Figure 3: ITC Distributional Decomposition

3a) Observed and counterfactual distributions



3b) Residual difference between lower income and counterfactual distributions



Higher income group re-weighted to have predictor profiles of lower-income group

Supplementary Table 1: Association between Income and Body Mass Index (BMI) z-score

	BMI z-score < -2 "Underweight"[1]	BMI z-score ≥ 1 to 2 "Overweight"[1]	BMI z-score ≥2 "Obesity"[1]
Unadjusted	RRR[2] (95% CI[3])	RRR (95% CI)	RRR (95% CI)
Income <$80,000	1.72 (0.67, 4.40)	1.46 (1.06, 2.01)	4.15 (2.37, 7.27)
Adjusted	RRR (95% CI)	RRR (95% CI)	RRR (95% CI)
Income <$80,000	1.46 (0.50, 4.28)	1.60 (1.11, 2.33)	3.01 (1.56, 5.82)
Child			
Age (months)	1.15 (1.01, 1.32)	0.98 (0.93, 1.04)	0.99 (0.90, 1.08)
Sex (male)	0.77 (0.30, 1.99)	1.14 (0.84, 1.55)	1.81 (0.99, 3.29)
Birthweight (kg)	0.31 (0.18, 0.56)	1.80 (1.38, 2.34)	1.20 (0.76, 1.89)
Total Months Breastfed	1.00 (0.96, 1.05)	0.99 (0.97, 1.01)	0.97 (0.94, 1.01)
Living Arrangement	1.06 (0.41, 2.75)	0.59 (0.37, 0.95)	0.85 (0.45, 1.60)
Parent			
Maternal Age at Birth	1.02 (0.93, 1.11)	0.97 (0.94. 1.00)	0.99 (0.94,1.06)
Maternal Education	2.81 (0.31, 25.27)	0.69 (0.41. 1.15)	0.55 (0.26, 1.17)
Maternal BMI	0.98 (0.88. 1.09)	1.06 (1.03. 1.09)	1.11 (1.06, 1.16)
Mother Born in outside Canada	0.92 (0.31, 2.74)	0.65 (0.44. 0.98)	1.49 (0.76, 2.92)
Maternal Ethnicity non-European	2.14 (0.73, 6.27)	0.77 (0.51, 1.16)	0.70 (0.35, 1.41)

[1] This multinomial regression used four categories of BMI as the outcome: <-2 "underweight"; ≥-2 to 1 "normal weight"; ≥ 1 to 2 "overweight"; ≥ 2 "obesity". The reference group was the "normal weight" category. [2]RRR: Relative Risk Ratio; [3]95% CI: 95% Confidence Interval

Supplementary Table 2: Association between Income and Strengths and Difficulties Questionnaire (SDQ) Total Difficulties Score

	SDQ Quartile 2[1]	SDQ Quartile 3[1]	SDQ Quartile 4
Unadjusted	RRR[2] (95% CI[3])	RRR (95% CI)	RRR (95% CI)
Income <$80,000	0.63 (0.33, 1.22)	1.69 (0.94, 3.03)	1.88 (1.06, 3.33)
Adjusted	RRR (95% CI)	RRR (95% CI)	RRR (95% CI)
Income <$80,000	0.49 (0.23, 1.03)	1.46 (0.73, 2.89)	1.35 (0.68, 2.65)
Child			
Age (months)	0.99 (0.97, 1.01)	0.98 (0.97, 1.00)	0.99 (0.97, 1.00)
Sex (male)	1.09 (0.71, 1.66)	1.15 (0.73, 1.81)	1.53 (0.97, 2.40)
Birthweight (kg)	0.95 (0.66, 1.37)	1.06 (0.72, 1.57)	0.98 (0.66. 1.44)
Living Arrangement	2.84 (0.73, 11.11)	3.26 (0.83, 12.86)	3.84 (1.01, 14.66)
Parent			
Maternal Age at Birth	0.97 (0.92, 1.02)	0.97 (0.91, 1.02)	0.95 (0.90, 1.01)
Maternal Education	0.53 (0.28, 0.99)	0.79 (0.40, 1.54)	0.63 (0.33, 1.20)
Mother Born in outside Canada	0.85 (0.50, 1.46)	0.83 (0.78, 1.47)	0.91 (0.52, 1.59)
Maternal Ethnicity non-European	0.96 (0.58, 1.59)	1.18 (0.70, 2.00)	1.09 (0.64, 1.86)

[1] This multinomial regression used four quartiles of SDQ Total Difficulties Score as outcome, with the first quartile as reference.
[2]RRR: Relative Risk Ratio; [3]95% CI: 95% Confidence Interval

Supplementary Table 3: Association between Income and Total Infant Toddler Checklist (ITC) Score

	ITC Quartile 2[1]	ITC Quartile 3[1]	ITC Quartile 4[1]
Unadjusted	RRR[2] (95% CI[3])	RRR (95% CI)	RRR (95% CI)
Income <$80,000	0.82 (0.55, 1.22)	0.46 (0.28, 0.74)	0.35 (0.21, 0.57)
Adjusted	RRR (95% CI)	RRR (95% CI)	RRR (95% CI)
Income <$80,000	1.13 (0.69, 1.84)	0.53 (0.30, 0.95)	0.44 (0.25, 0.80)
Child			
Age (months)	1.29 (1.05, 1.59)	1.25 (1.00, 1.57)	1.56 (1.27, 1.93)
Sex (male)	0.55 (0.38, 0.78)	0.64 (0.43, 0.94)	0.45 (0.30, 0.66)
Birthweight (kg)	1.56 (1.14, 2.13)	1.39 (0.98, 1.95)	1.67 (1.20, 2.33)
Preterm	0.96 (0.54, 1.69)	1.54 (080, 2.97)	2.14 (1.06, 4.31)
Living Arrangement	0.93 (0.53, 1.61)	0.48 (0.19, 1.21)	1.17 (0.65, 2.10)
Parent			
Maternal Age at Birth	0.94 (0.90, 0.98)	0.90 (0.86, 0.95)	0.95 (0.91, 0.99)
Maternal Education	2.01 (1.19, 3.38)	1.48 (0.84, 2.61)	1.42 (0.82, 2.46)
Mother Born in outside Canada	0.91 (0.62, 1.33)	0.81 (0.54, 1.22)	0.84 (0.57, 1.26)
Maternal Ethnicity non-European	0.67 (0.44, 1.00)	0.77 (0.50, 1.19)	0.57 (0.36, 0.88)

[1] This multinomial regression used four quartiles of Total ITC Score as outcome, with the first quartile as reference. [2]RRR: Relative Risk Ratio; [3]95% CI: 95% Confidence Interval

STROBE Statement—Checklist of items that should be included in reports of ***cross-sectional studies***

	Item No	Recommendation	Page No
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	3
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	3-4
Objectives	3	State specific objectives, including any prespecified hypotheses	4
Methods			
Study design	4	Present key elements of study design early in the paper	5
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	5
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants	5
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	5-7
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	5-7
Bias	9	Describe any efforts to address potential sources of bias	7-8
Study size	10	Explain how the study size was arrived at	8
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	7-8
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	7-8
		(*b*) Describe any methods used to examine subgroups and interactions	7-8
		(*c*) Explain how missing data were addressed	7-8
		(*d*) If applicable, describe analytical methods taking account of sampling strategy	
		(*e*) Describe any sensitivity analyses	8
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	8, Figure 1
		(b) Give reasons for non-participation at each stage	N/A
		(c) Consider use of a flow diagram	Figure 1
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	9, Table 1
		(b) Indicate number of participants with missing data for each variable of interest	
Outcome data	15*	Report numbers of outcome events or summary measures	Table 1

Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	N/A
		(*b*) Report category boundaries when continuous variables were categorized	N/A
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	N/A
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	
Discussion			
Key results	18	Summarise key results with reference to study objectives	11
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	13-14
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	14
Generalisability	21	Discuss the generalisability (external validity) of the study results	14
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	1

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.