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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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ABSTRACT

Objectives Children from low-income households are at an increased risk of social, behavioural 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 vs low): body mass index (BMI), behaviour 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, dichotomised at the median income for Toronto (<$C80 000 or ≥$C80 000). Outcomes were: (1) growth (BMI z-score (zBMI) at 5 years, 1628 participants); (2) behaviour (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 favourable than their observed distributions.

Conclusion Comparing the distributions of child health outcomes and understanding different risk profiles for children from higher-income 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

- 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.
- Limits to generalisability 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 behavioural 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 categorised 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), behaviour 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 standardised 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 to 2019. The study protocol and sample population have been described in detail.[14]

Exclusion criteria at enrolment 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.

Patient and public involvement

The TARGet Kids! Research Network includes a Parent and Clinician Team 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 standardised 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 $C10 000' to 'greater than $C500 000'. We created two categories, dichotomised at approximately the median household income in the Toronto Census Metropolitan Area based on the 2016 Canadian census (<$C80 000 or ≥$C80 000).We dichotomiSed 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 (BMI z-score (zBMI) at 5 years); (2) child behaviour (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 metres and measured at 5 years old. Age and sex standardised zBMI was calculated using the recommended WHO growth standards.[18]

To assess child behaviour, we used the 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 composed 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 ITC (also known as the Communication and Symbolic Behaviour 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, birth weight (kilograms) and living arrangement (living with both parents or any other arrangement) for all models; gestational age (32–36 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 BMI (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 characterise the study population and describe the means and proportions of the outcomes of interest. We used Mann-Whitney U test and χ^2 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 distributional 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 reweighted counterfactual distribution to compare it visually to the original distributions for the higher-income 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 reweighting 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 reweighted 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 zBMI 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).[26]

RESULTS

For the BMI outcome 2123 children between 60 and 71 months had complete outcome and income reported, of whom 1628 (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

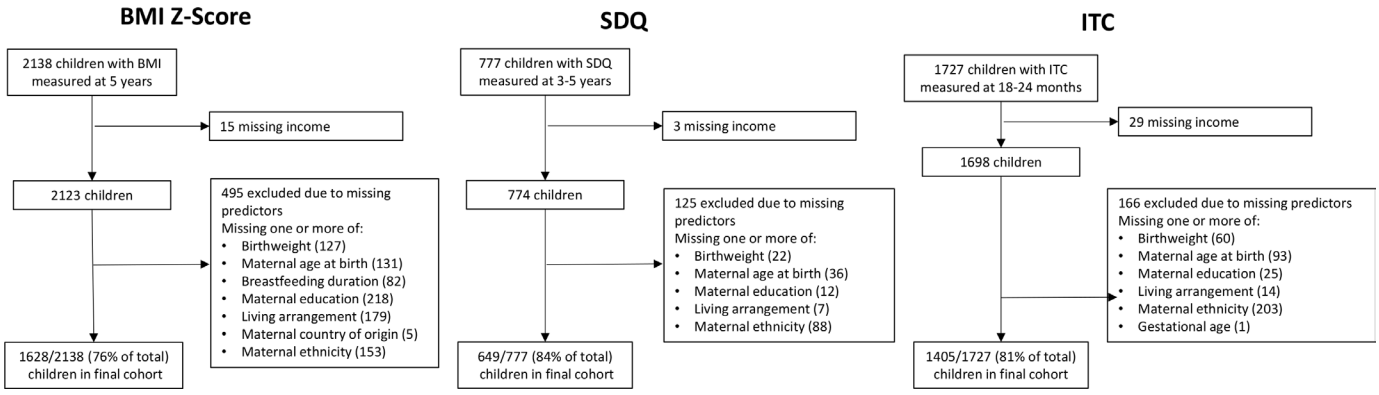

Figure 1 These flow diagrams show cohort definitions for each outcome and reasons for participant exclusion due to missing data. BMI, body mass index; ITC, Infant Toddler Checklist; SDQ, Strengths and Difficulties Questionnaire.

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). Kolmogorov Smirnov Test (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 reweighted to have the predictor profiles of children from higher-income households, the distribution of zBMI within the normal range (−1 to 1) narrowed. This reweighted distribution is shown with the observed distributions in figure 2C. The residual, unexplained difference between the reweighted 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 reweighted 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 reweighted 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 reweighted 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 reweighted distribution is shown with the observed distributions in figure 4C. However, as total ITC score decreases into higher risk ranges, the reweighted distribution still shows a greater proportion of children from low-income households with lower scores. The residual, unexplained difference between the reweighted distribution and the high-income distribution is shown in figure 4D.

Sensitivity analyses

Our sensitivity analysis, presented in online supplemental 1, which reweighted the predictor profiles of children from higher-income households to have the predictor

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

Characteristic, n (%)	BMI (n=1628)			SDQ (n=649)			ITC (n=1405)		
Predictors	**Full sample (n=1628)**	**Income ≥$C80 000 (n=1180)**	**Income <$C80 000 (n=448)**	**Full sample (n=649)**	**Income ≥$C80 000 (n=539)**	**Income <$C80 000 (n=110)**	**Full sample (n=1405)**	**Income ≥$C80 000 (n=1106)**	**Income <$C80 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 (55.6)	615 (51.5)	154 (51.5)
Birth weight (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)	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)	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)

BMI, body mass index; ITC, Infant Toddler Checklist; SDQ, Strengths and Difficulties Questionnaire.

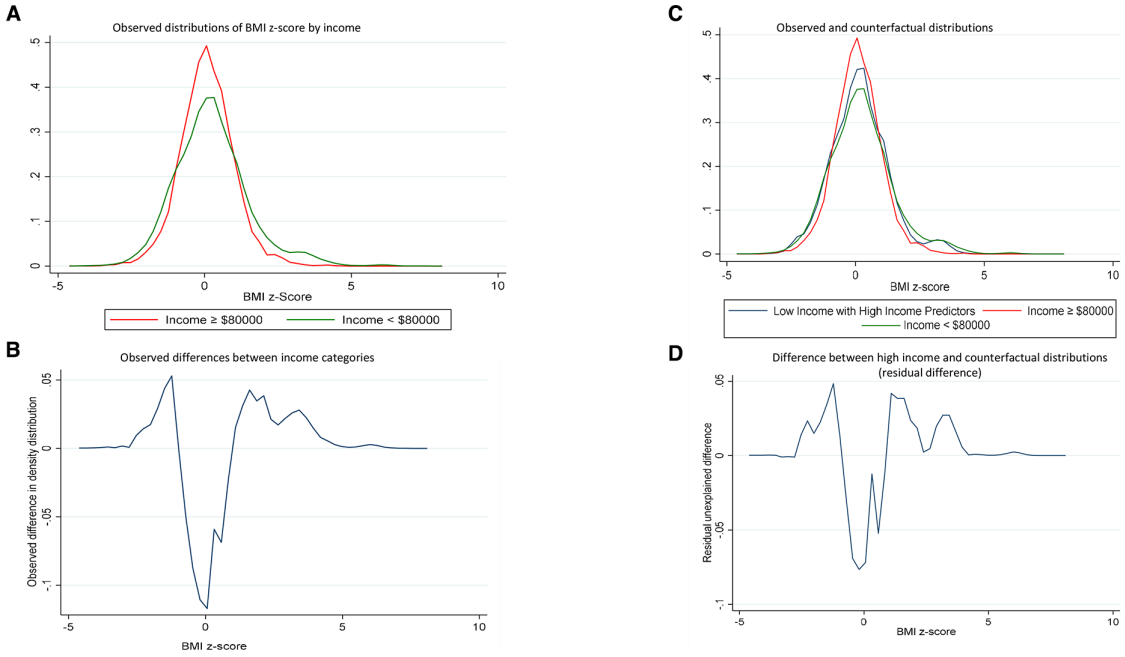

Figure 2 Distributions and distributional decomposition of BMI z-score, including observed distributions of BMI z-score by income (A); differences between observed distributions (B); observed distribution plus the counterfactual distribution of the low-income group with predictor profile of high-income group (C); and the residual difference between the high-income and counterfactual distributions (D). BMI, body mass index.

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 online supplemental 2. The models generally demonstrate that lower income is associated with higher

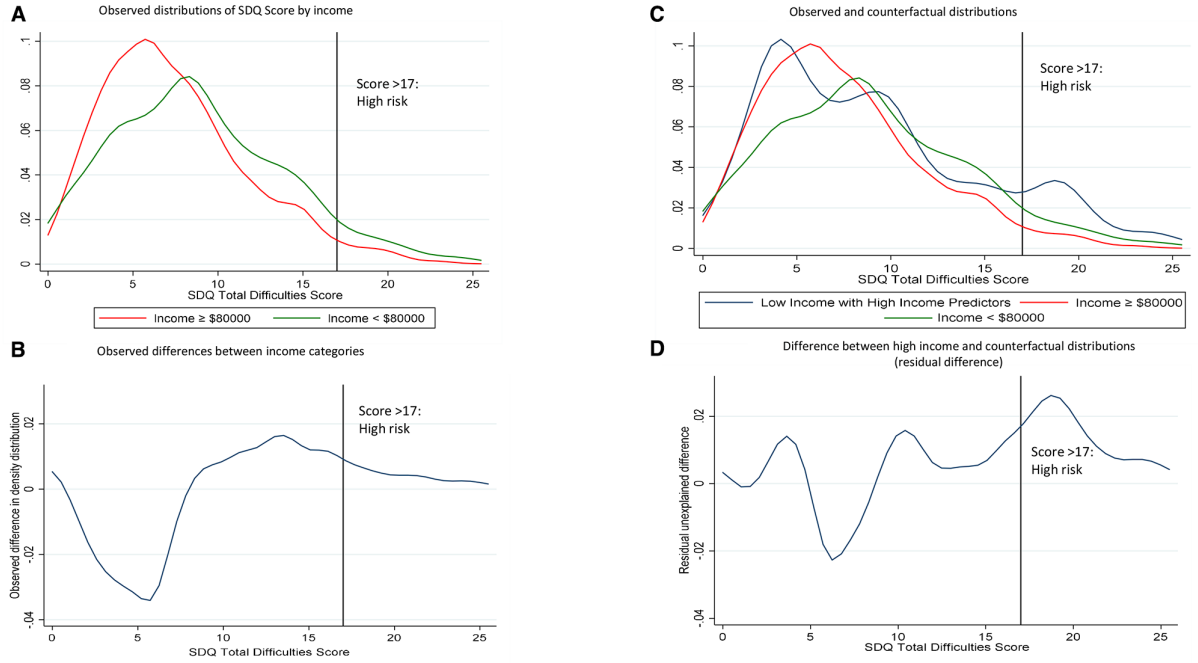

Figure 3 Distributions and distributional decomposition of SDQ Total Difficulties Score, including observed distributions of Total Difficulties Score by income (A); differences between observed distributions (B); observed distribution plus the counterfactual distribution of the low-income group with predictor profile of high-income group (C); and the residual difference between the high-income and counterfactual distributions (D). SDQ, Strengths and Difficulties Questionnaire.

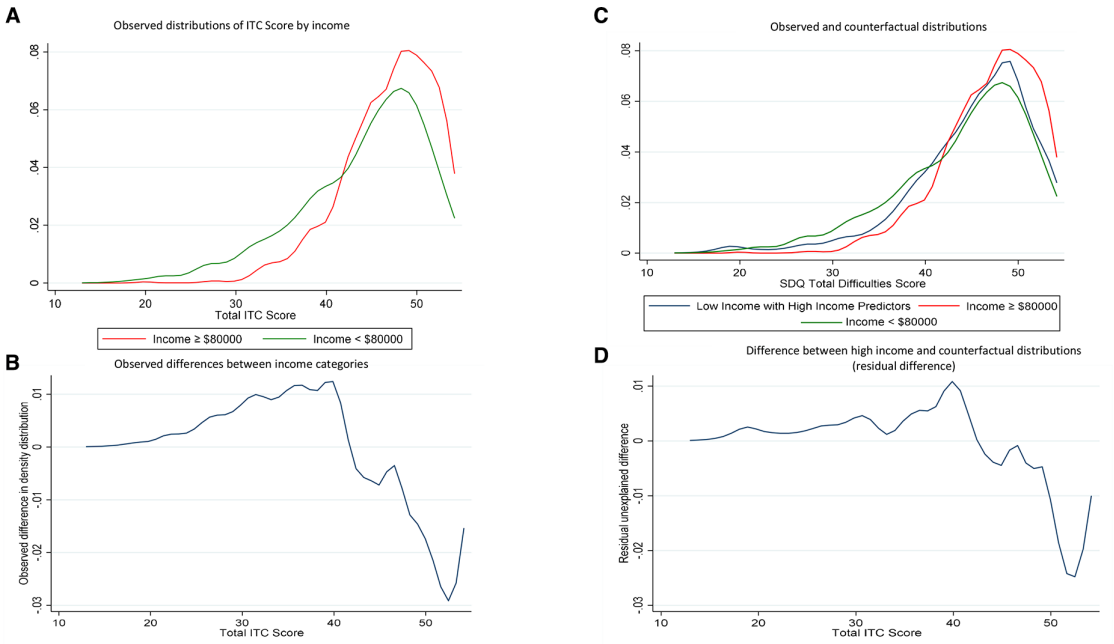

Figure 4 Distributions and distributional decomposition of total ITC Score, including observed distributions of ITC Score by income (A); differences between observed distributions (B); observed distribution plus the counterfactual distribution of the low-income group with predictor profile of high-income group (C); and the residual difference between the high-income and counterfactual distributions (D). ITC, Infant Toddler Checklist; SDQ, Strengths and Difficulties Questionnaire.

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-income and lower-income households for three important outcomes studied: zBMI, total behavioural 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 reweighted 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 reweighting, children in the lower-income group with behavioural 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 reweighted 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 behaviour 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, visualising 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, behaviour or development are different than the determinants of where an individual falls in the lower risk range. For example, clinically significant behaviour difficulties on the SDQ may represent an underlying behaviour

disorder such as attention–deficit disorder, while within the low-risk range, other factors such as parenting behaviours, 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 with zBMI, routine predictors of child behaviour 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 reweighted 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 reweighted counterfactual. Future research could explore alterative categories of income. There was a smaller proportion of participants with certain characteristics which required categorisation 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 with 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, behaviour 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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