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**Manuscript Title:** Income gains predict cognitive functioning longitudinally throughout later childhood in poor children

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### Abstract

Alleviating disadvantage in low-income environments predicts higher child cognition in early childhood. It is less established whether family income continues to predict cognitive growth in later childhood or whether there may even be bidirectional dynamics. Importantly, living in poverty may moderate income-cognition dynamics. This study investigates longitudinal dynamics in 7 waves of data from 1168 children aged 4.6 to 12 years, 226 (19%) of which lived in poverty in at least one wave, in the NICHD Study of Early Child Care and Youth Development. Two sets of dual change score models evaluated, first, whether a *score* predicted *change* from that wave to the next and, second, whether *change* from one wave to the next predicted the following *score*. As previous comparisons have documented, poor children had substantially lower average starting points and cognitive growth slopes through later childhood. The first set of models showed that income *scores* did not predict cognitive *change*. Interestingly, child cognitive scores positively predicted income change in reverse. We speculate that parents may reduce their work investment, thus reducing income gains, when their children fall behind. Second, income *changes* continued to positively predict higher cognitive *scores* at the following wave for poor children only. This suggests income gains and losses continue to be a leading indicator in time of poor children's cognitive performance in later childhood. This study underlined the need to look at changes in income, allow for poverty moderation, and explore bidirectional income-cognition dynamics in middle childhood.

**Keywords:** socioeconomic status, income, cognition, child development, longitudinal models

## Introduction

Children's cognitive performance robustly varies along gradients of socioeconomic status (SES), most commonly indicated by family income, parental education and occupation, with lower SES children scoring over one standard deviation lower on reading and math achievement tests (Duncan & Magnuson, 2011). Longitudinal research investigating SES and cognitive development across childhood is recently accumulating. Studies show that children of lower SES have lower initial levels and slopes of intelligence (von Stumm & Plomin, 2015), executive functions and self-regulation (Hackman, Gallop, Evans, & Farah, 2015; Montroy, Bowles, Skibbe, McClelland, & Morrison, 2016), as well as verbal comprehension and math ability (Crosnoe, Leventhal, Wirth, Pierce, & Pianta, 2010; Hair, Hanson, Wolfe, & Pollak, 2015; Network., 2005; Wang et al., 2017), and the disparities in math ability are partially mediated by executive functions (Lawson & Farah, 2017). Correspondingly, disparities in different cognitive and academic outcomes along gradients of parental education are largely driven by a single developmental pathway manifest in global cognitive development, yet, math ability has an additional unique pathway (Tucker-Drob, 2013). Furthermore, cognitive disparities widen across childhood (Carneiro & Heckman, 2003; Cunha, Heckman, Lochner, & Masterov, 2006; Moffitt et al., 2011; von Stumm & Plomin, 2015) and rank-order stability of cognitive performance is very high by the end of the first decade of life (Tucker-Drob & Briley, 2014). Additional evidence is amassing to suggest that SES differences in cognitive functions are found in the brain structures that support them (Hair et al., 2015; Hanson, Chandra, Wolfe, & Pollak, 2011; Jednoróg et al., 2012; Luby et al., 2013; Noble et al., 2015; Noble, Grieve, et al., 2012; Noble, Houston, Kan, & Sowell, 2012; Rao et al., 2010; Yu et al., 2017), as early as 1 month in healthy infants

(Betancourt et al., 2016), and at 6 months in functional brain activity (Tomalski et al., 2013). Collectively, these studies suggest that between-person SES-related disparities in neural and cognitive functioning are found early in ontogenetic development and widen over early and middle childhood, reaching high levels of stability in between-person rank-order by later childhood.

Importantly, most of these studies are genetically uninformed, although heritability studies estimate that up to 70% of the variation in cognition is attributable to additive genetic variation by adolescence (Tucker-Drob & Briley, 2014), and thus do not provide evidence for environmental- or genetically-mediated causation (Ericsson et al., 2017; Spinath & Bleidorn, 2017). Nevertheless, longitudinal mediation (Hackman et al., 2015), adoption studies (Capron & Duyme, 1989; Kendler, Turkheimer, Ohlsson, Sundquist, & Sundquist, 2015; van IJzendoorn, Juffer, & Poelhuis, 2005), (quasi-)experimental and intervention studies (Costello, Compton, Keeler, & Angold, 2003; Duncan et al., 1998; Heckman, 2006) and genetically informed studies (Tucker-Drob & Briley, 2014; Tucker-Drob, Briley, & Harden, 2013; Tucker-Drob & Harden, 2012b) provide evidence that environments along SES strata are also likely to play a causal role in childhood cognitive development. Thus, cognitive disparities along the SES gradient are explained by both environmentally- and genetically-mediated effects, which are known to interact and correlate in ways we do not yet fully comprehend (Scarr & McCartney, 1983).

Furthermore, the coupled dynamic relationship of SES indicators and cognition has rarely been studied, because SES indicators have been treated as static predictors of child outcomes (Crosnoe et al., 2010; Lawson & Farah, 2017; von Stumm & Plomin, 2015; Wang et al., 2017). Yet, SES indicators, especially income, also change over time (Duncan, Ziol-Guest, & Kalil, 2010). Very few studies have

begun to look at *change* in income (Duncan et al., 2017, 1998). For instance, change in income-to-needs predicts child cognition at age 3 for poor, but not never poor, families in the National Institute of Child Health and Human Development (NICHD) Study of Early Child Care and Youth Development (SECCYD) (Dearing, McCartney, & Taylor, 2001; Mistry, Biesanz, Taylor, Burchinal, & Cox, 2004). Furthermore, children of families that had lower income-to-needs in middle childhood than in early childhood had lower slopes in planning efficiency from ages 4.6 to 9 years in the same sample (Hackman et al., 2015). In addition, quasi-experimental studies suggest that income received when a child is young (ages 0-5 years) has stronger lasting impacts on cognitive and school achievement than does income received during later childhood or adolescence (Duncan, Brooks-Gunn, & Klebanov, 1994; Duncan et al., 1998). Therefore, previous research has shown that changes in income during early childhood predict child cognition, more so for families living in poverty. It is less established whether family income changes in later childhood and adolescence continue to predict cognitive functioning. Importantly, research analysis of repeated, time-lagged measurements with structural equation models (SEM) strengthen inferences on bivariate relationships (Adler & Rehkopf, 2008; Hamaker, Kuiper, & Grasman, 2015).

In addition to largely neglecting the effect of changes in income onto cognition, the SES–cognitive development literature has ignored potential effects of children on their parents’ ability to earn income. However, given evocative and bidirectional effects between children’s behaviors and their parents’ parenting styles and psychological well-being as well as their shared genes (Bradley & Corwyn, 2013; Miner & Clarke-Stewart, 2008; Pike, McGuire, Hetherington, Reiss, & Plomin, 1996; Tucker-Drob & Harden, 2012a), it is possible that children also influence family

income. We know of no study exploring bidirectional dynamics between income and child cognition.

Therefore, this study aims to investigate the dynamic relationship between family income and child verbal comprehension and math ability over middle childhood and early adolescence. Verbal comprehension and math skills are two cognitive domains that are highly correlated over time, but they also develop as separate trajectories (Ferrer & McArdle, 2004) that may be differentially related to changes in income (Tucker-Drob, 2013). Here, we estimated longitudinal dual change score models (DCSMs) in 1168 NICHD SECCYD children aged 4.6 to 12 years (see *Data Analysis* section). DCSMs are latent-change SEMs separating between-person trait-like differences from between-person differences in within-person change across time (Ferrer & McArdle, 2010; Hishinuma, Chang, McArdle, & Hamagami, 2012). This allows us to explore coupling dynamics (also called cross-lagged effects) between income and cognition. First, following DCSM modeling convention, we explore whether a *score* in one variable predicts *change* in the other variable from that wave to the next. Second, given previous research on income change, we investigate whether *change* in one variable from one wave to the next predicts the following *score* in the other variable. Importantly, we tested whether living in poverty moderates income–cognition dynamics in DCSMs split by a poor/never poor grouping. The following two specific research questions were addressed in the current study:

1. Are there *score-to-change* couplings from income to cognition and vice versa in middle childhood and early adolescence that are moderated by living in poverty?
2. Are there *change-to-score* couplings from income to cognition and vice versa in middle childhood and early adolescence that are moderated by living in poverty?

## Method

### Participants

Families in the NICHD SECCYD were recruited shortly after the birth of a child in 1991 at 10 sites across the United States (Little Rock, AR; Irvine, CA; Lawrence, KS; Boston, MA; Philadelphia, PA; Pittsburgh, PA; Charlottesville, VA; Morganton, NC; Seattle, WA; and Madison, WI). Study procedures were approved by the institutional review boards at the 10 NICHD SECCYD study sites and informed consent was obtained from all participating families. During 24-hour recruitment windows, all women giving birth in the selected hospitals were screened for eligibility and willingness to participate. 1168 (48% female) of the final sample of 1364 children contributed to the data reported here, including 24% ethnic minority children, 11% mothers who had not completed high school, and 14% single-parent mothers. Mothers had an average of 14.4 years of education (for more sample information see NICHD Early Child Care Research Network., 2004). Average family income-to-needs (calculated by dividing income by the poverty threshold for a household given the year and number of household members) was 4 times the poverty threshold over the reported timeframe (mean = 4.1, SD = 3.28). 19% of the study sample lived below the poverty threshold in at least one wave of the reported timeframe, which is similar to US population estimates at 19% for children under age 6 (Proctor & Dalaker, 2003). Therefore, the NICHD SECCYD sample can be described as predominantly 'middle class', but also includes a substantial proportion of families intermittently living in poverty. Additional details about procedures of data collection can be found on the study's website (<https://www.nichd.nih.gov/research/supported/seccyd/Pages/overview.aspx>).

Descriptive statistics for measures of interest and correlations across time are displayed in Table 1 and 2, respectively.

This study was approved by the local ethics commission (Max Planck Institute for Human Development, “Longitudinal dynamics of family income and child behavioral development”, 08/12/2015).



Table 1

*Descriptive statistics for income, log income, verbal comprehension, and math ability at each data collection wave for poor and never poor groups.*

	Poor			Never Poor		
	Median	<i>SD</i>	<i>N</i>	Median	<i>SD</i>	<i>N</i>
1 Income <sup>a</sup>	1244	1159	213	4416	4128	860
2 Income	1041	1213	194	4583	3620	834
3 Income	1458	1220	180	5416	4212	803
4 Income	1875	1458	184	5416	5822	812
5 Income	1875	1589	195	6250	5987	803
6 Income	1875	1569	195	6250	6598	801
7 Income	1875	1769	196	6250	7345	799
1 Education <sup>b</sup>	12	1.96	226	14	2.42	942
1 Log Income <sup>c</sup>	-1	0.77	213	0.26	0.56	860
2 Log Income	-1.18	0.86	194	0.30	0.55	834
3 Log Income	-0.84	0.75	180	0.47	0.57	803
4 Log Income	-0.59	0.75	184	0.47	0.62	812
5 Log Income	-0.59	0.79	195	0.61	0.61	803
6 Log Income	-0.59	0.73	195	0.61	0.64	801
7 Log Income	-0.59	0.79	196	0.61	0.63	799
1 VC <sup>d</sup>	451	12.64	212	465	13.37	848
3 VC	476	12.58	200	486	11.29	820
4 VC	490	12.65	195	497	10.33	819
6 VC	497	13.75	195	509	10.6	797
1 Math <sup>e</sup>	417	21.44	209	431	17.21	844
3 Math	458	14.80	202	473	14.79	821
4 Math	492	17.01	195	502	11.27	818
6 Math	502	16.27	195	514	10.72	798

<sup>a</sup>Income = Raw monthly pre-tax household income.

<sup>b</sup>Maternal education at children's birth. 12 = number of years in school, but no high school graduate; 14 = some college.

<sup>c</sup>Log income = Natural log transformed income standardized to wave 1 of the whole sample.

<sup>d</sup>VC (Verbal Comprehension) = Woodcock-Johnson Picture Vocabulary W score.

<sup>e</sup>Math = Woodcock-Johnson Applied Problems W score.

Table 2

*Correlations across time for log income, verbal comprehension, and math ability.*

	2 Inc	3 Inc	4 Inc	5 Inc	6 Inc	7 Inc	1 VC	3 VC	4 VC	6 VC	1 Ma	3 Ma	4 Ma	6 Ma
1 Inc <sup>a</sup>	0.86	0.81	0.77	0.77	0.75	0.70	0.38	0.36	0.36	0.35	0.39	0.35	0.37	0.39
2 Inc		0.88	0.83	0.80	0.76	0.72	0.35	0.34	0.36	0.34	0.36	0.34	0.36	0.41
3 Inc			0.88	0.84	0.79	0.76	0.38	0.36	0.34	0.34	0.34	0.34	0.32	0.36
4 Inc				0.90	0.85	0.83	0.38	0.39	0.37	0.37	0.36	0.38	0.36	0.41
5 Inc					0.90	0.85	0.38	0.41	0.36	0.38	0.38	0.38	0.37	0.43
6 Inc						0.88	0.37	0.38	0.37	0.37	0.39	0.37	0.36	0.42
7 Inc							0.36	0.37	0.33	0.34	0.37	0.34	0.30	0.38
1 VC <sup>b</sup>								0.65	0.61	0.61	0.53	0.43	0.43	0.44
3 VC									0.73	0.71	0.46	0.49	0.48	0.51
4 VC										0.79	0.45	0.47	0.55	0.53
6 VC											0.45	0.48	0.54	0.58
1 Ma <sup>c</sup>												0.60	0.56	0.56
3 Ma													0.69	0.70
4 Ma														0.78

<sup>a</sup>Inc = log transformed family income.

<sup>b</sup>VC (Verbal Comprehension) = Woodcock-Johnson Picture Vocabulary W score.

<sup>c</sup>Ma (Math Ability) = Woodcock-Johnson Applied Problems W score.

<sup>d</sup>Pearson's correlations are for standardized values.

<sup>e</sup>All correlations are significant at the  $\alpha$  level of 0.05.

## **Measures**

### *Income*

Family income was calculated at all 7 waves (4.6 years, kindergarten (6 years), grade 1 (7 years), grade 3 (9 years), grade 4 (10 years), grade 5 (11 years), grade 6 (12 years)). Mothers reported on their and their partner's annual pre-tax employment income by circling one of 22 income ranges that included the family income. Total family income was computed as the midpoint of the range circled by the respondent. Income was log transformed to correct for significant skew and then standardized to wave 1 of the whole sample (mean = 0, SD = 10) so that wave 1 functioned as the baseline to model changes from this baseline for each group and multiplied by 10 to improve estimation of stable variance parameters without affecting model statistics (Small, Dixon, McArdle, & Grimm, 2013).

### *Poverty Grouping*

Poor versus never poor grouping was based on a family income-to-needs being below 1 at any of the 7 waves (poor) versus at none of the 7 waves (never poor). An income-to-needs score of 1 indicates that the family's income meets the federal poverty threshold for a family of that size in that year. This resulted in 226 children (19%) that lived below the poverty threshold in at least one wave versus 942 children (81%) that never lived below the poverty threshold between ages 4.6 and 12 years. This means 'never poor' refers to the reported timeframe only, since 5% (n=46) of the 'never poor' families in late childhood lived below the poverty threshold in at least one wave before age 4.6. This grouping was chosen to look at the effects of income during later childhood specifically. Further, 6% (n=14) of the poor children lived in chronic poverty at all 7 waves.

*Cognition*

Two Woodcock–Johnson Psycho-Educational Battery–Revised subtests (WJ–R; Woodcock & Johnson, 1989) were assessed in the laboratory at four waves (4.6 years, grade 1 (7 years), grade 3 (9 years), grade 5 (11 years)). Verbal comprehension was assessed with the Picture Vocabulary subtest requiring children to name familiar and unfamiliar pictured objects. Math ability was assessed with the Applied Problems subtest requiring a participant to read a problem, decide which mathematical operation to use, and complete necessary calculations. Raw scores on the subtests were converted to W scores to norm them across the age range for ease of interpretation across multiple administrations by transformation of the Rasch ability scale that centered the raw score at 5<sup>th</sup> grade (score of 500). Each cognitive measure was standardized for the whole sample to wave 1 (mean = 0, SD = 10) and multiplied by 10 for modeling.

*Maternal education*

Maternal education was obtained during study recruitment only and was scored as: less than 12 = number of years in school, 13 = high school graduate or GED, 14 = some college, 16 = a bachelor's degree, 17 = some graduate school experience, 18 = a master's degree, 19 = a law school degree, and 21 = more than one master's degree or a doctoral degree. Maternal education was mean centered (corresponding to 13=high school graduate or GED).

**Data Analysis**

The NICHD SECCYD sample provided the opportunity to apply sophisticated statistical techniques, given the large sample size and multiple repeated measures.

Wave based models were fitted on 7 waves of data collected in regular time intervals of approximately 1 year to 1.5 years (4.6 years, kindergarten (6 years), grade 1 (7 years), grade 3 (9 years), grade 4 (10 years), grade 5 (11 years), grade 6 (12 years)) with a latent replacement for grade 2 (8 years) added to all models.

As a first modeling step, income and cognition were fit as univariate models to the entire sample comparing four statistically nested models: (1) intercept only, (2) intercept and proportional change, (3) intercept and slope, and (4) DCSMs (intercept, proportional change, and slope). Indeed, DCSMs with gender and maternal education covariates on latent level and slope factors best fit the data.

DCSMs (Ferrer & McArdle, 2010; Hishinuma, Chang, McArdle, & Hamagami, 2012) encompass latent-change SEMs and autoregressive time series models and can be thought of as closely related to random-intercept cross-lagged panel models (Hamaker et al., 2015). Individual growth is described by the level at the beginning of the observation period (intercept,  $I$ ) and a person's change over time, which is identified as the unobserved difference between the initial observation and subsequent observations ( $\Delta$ ). The random intercept ( $I$ ) is modeled with variance to indicate there are between-person differences in starting points. The change score is identified with two components: First, the proportional change component ( $\beta$ ) identifies how previous scores influence change between measurement periods (autoregressive). Second, the slope ( $S$ ) captures a linear growth component that has previously been observed in cognitive development (Grimm, 2007). The random slope component is varied between persons, while the proportional change component is a fixed effect. Within-person changes from wave-to-wave are thus directly modeled and present the combination of these two components ( $\beta$ ,  $S$ ). The overall effect of change may be positive or negative depending on parameter estimates and previously

observed scores. Further, the DCSM separates measurement error ( $\sigma$ ) implicit in task performance, which is important for cognitive tasks from a theoretical point of view (Ferrer & McArdle, 2010).

In the second step, univariate DCSMs were estimated as multigroup models that allowed latent means, variances and covariances to differ between poor/ never poor groups. In a third step, those models were combined in bivariate multigroup DCSMs of income-cognition, including estimated covariance parameters between the intercept and slope factors ( $\rho$ ) and, concerning our first aim, score-onto-change coupling parameters (see Figure 1) that were allowed to differ between groups. This coupling parameter is a fixed effect that represents the time-dependent effect of one construct on the subsequent change in the other (McArdle, 2009). Thus, evaluation of score-onto-change coupling allow for inferences to be made between income at wave 1 being a leading indicator in time of wave-1-to-wave-2 changes in cognition ( $\gamma_{\text{income score} \rightarrow \text{cognition change}}$ ) and vice versa ( $\zeta_{\text{cognition score} \rightarrow \text{income change}}$ ). In a fourth step addressing our second aim, the bivariate models of income-cognition estimated covariances and change-onto-score coupling parameters (see Figure 2) that were allowed to differ between groups. Evaluation of change-onto-score coupling parameters allow for inferences to be made between income changes from wave-1-to-wave-2 being a leading indicator in time of cognition scores at wave 2 ( $\kappa_{\text{income change} \rightarrow \text{cognition score}}$ ) and vice versa ( $\theta_{\text{cognition change} \rightarrow \text{income score}}$ ). Including covariates as predictors of slopes allows us to examine income-cognition coupling effects whilst accounting for stable slope differences along gradients of maternal education and gender.

Models were compiled and evaluated using MPlus 7.4 (Muthén & Muthén, 2014) and fitted using full information maximum likelihood (FIML) estimation to

accommodate missing at random data. Models were evaluated with the Chi-Squared ( $\chi^2$ ) likelihood ratio test, the Akaike information criterion (AIC), comparative fit index (CFI), and the root mean square error of approximation ( $E_a$ ) with Confidence Intervals of 95% to determine the most parsimonious model. We report the  $\chi^2$ , CFI, AIC and  $E_a$  as indices of fit. We report standardized parameter estimates as effect sizes and parameter significance is denoted if  $\Delta\chi^2$  is significant at  $\alpha = 0.05$  comparing the parameter freed versus fixed to 0 ( $\Delta df = 1$ ).

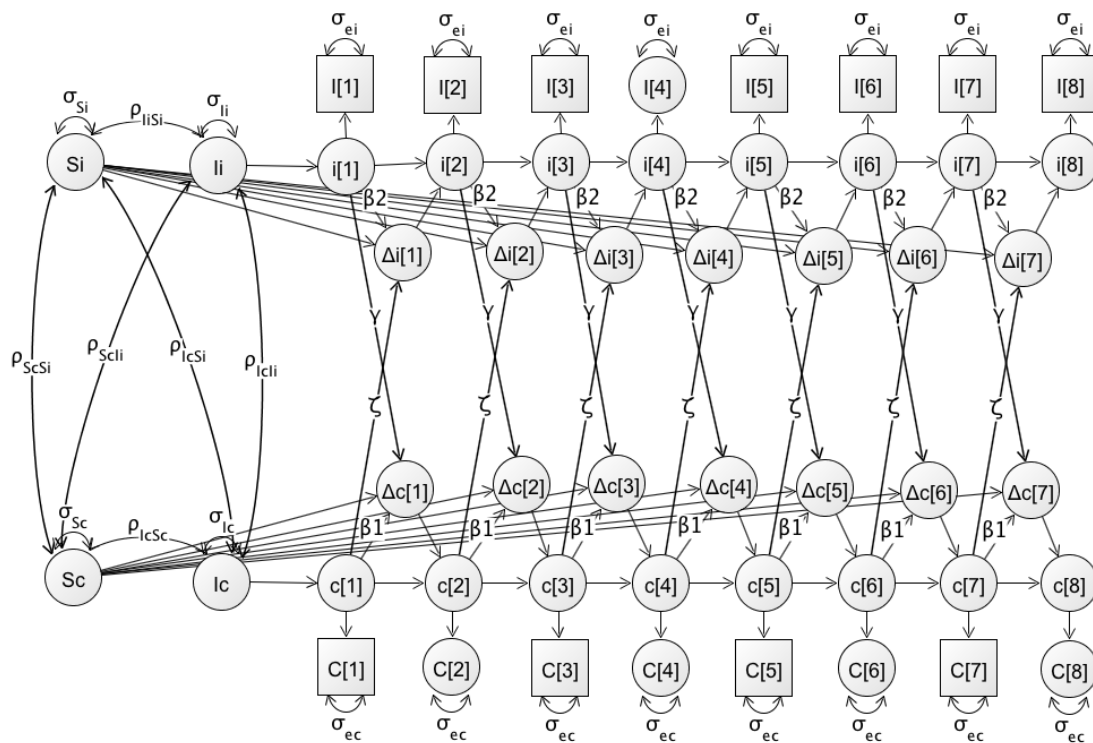


Figure 1. Bivariate score-onto-change coupling model.

Graphical representation of bivariate dual change score models of cognition (C) and income (I) in approximately one-year intervals from age 4.6 to 12 years with latent replacements for missing time points as implemented here. Observed variables are depicted as squares, latent variables as circles, regressions as one-headed arrows, and variances and covariances as two-headed arrows. Paths without values were fixed at

1. Model includes estimated covariance parameters between the intercept and slope factors ( $\rho$ ) and score-onto-change coupling parameters ( $\gamma_{\text{income score} \rightarrow \text{cognition change}}$ ,  $\zeta_{\text{cognition score} \rightarrow \text{income change}}$ ). Actual models included means and gender and maternal education as covariates and were run as multigroup models of poor/never poor groups, which was not shown for simplicity of model interpretation. Figure compiled using Onyx 1.0 (<http://onyx.brandmaier.de>).

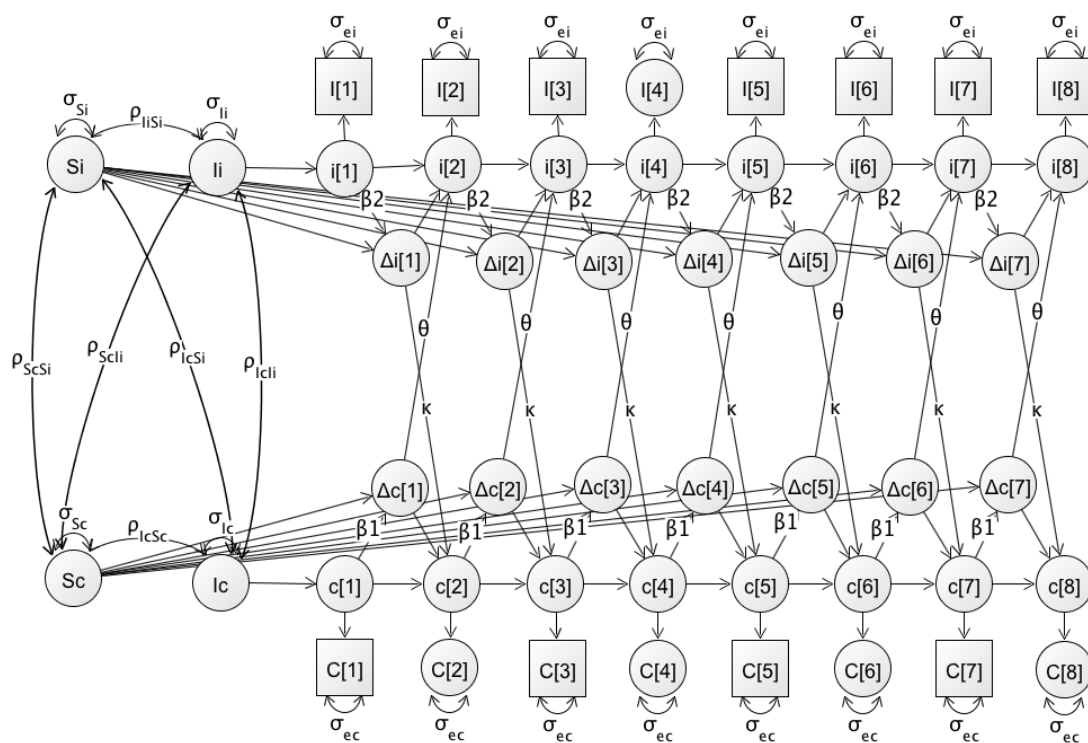


Figure 2. Bivariate change-onto-score coupling model.

Graphical representation of bivariate dual change score models of cognition (C) and income (I) in approximately one-year intervals from age 4.6 to 12 years with latent replacements for missing time points as implemented here. Observed variables are depicted as squares, latent variables as circles, regressions as one-headed arrows, and variances and covariances as two-headed arrows. Paths without values were fixed at 1. Model includes estimated covariance parameters between the intercept and slope



factors ( $\rho$ ) and change-onto-score coupling ( $\kappa_{\text{income change} \rightarrow \text{cognition score}}, \theta_{\text{cognition change} \rightarrow \text{income score}}$ ). Actual models included means and gender and maternal education as covariates and were run as multigroup models of poor/never poor groups, which was not shown for simplicity of model interpretation. Figure compiled using Onyx 1.0 (<http://onyx.brandmaier.de>).

## Results

### Descriptive Statistics and Missingness

Repeated measures of income and cognition were positively correlated between and within each construct (see Table 2). Cross-time correlations were significantly higher for income compared to cognitive outcomes (mean income  $r = 0.82$  versus verbal comprehension  $r = 0.68$ ,  $Z = 7.67$ ,  $p < 0.05$  and math ability  $r = 0.65$ ,  $Z = 8.94$ ,  $p < 0.05$ ). However, given that stability of constructs is explicitly modeled in such longitudinal models, we can compare bidirectional coupled parameters despite differences in temporal stability (Hamaker et al., 2015; McArdle, 2009).

Logistic regression analyses for the whole sample showed that those providing income data at wave 1 did not differ from families that did not in terms of their children's initial wave cognitive performance (all  $p$ 's  $> 0.16$ ). Missingness in cognitive variables at the final wave was not predicted by income or maternal education of the first wave and, in reverse, missingness in income at the last wave was not predicted by cognitive variables of the first wave (all  $p$ 's  $> 0.17$ ). Additionally, there was no mean difference in income or maternal education at the first wave between children who did and did not have missing cognitive values in the final wave (all  $p$ 's  $> 0.22$ ).

### Univariate DCSMs

Univariate DCSMs that allowed intercept and slope means, variances, covariances, maternal education covariate effects and residual variances to differ between poor/never poor groups provided good fit for income ( $\chi^2 = 227.77$ ,  $df = 75$ ,  $CFI = 0.98$ ,  $AIC = 40990$ ,  $E_a = 0.06$ ), verbal comprehension ( $\chi^2 = 44.90$ ,  $df = 19$ ,  $CFI = 0.99$ ,  $AIC = 26660$ ,  $E_a = 0.05$ ) and math ability ( $\chi^2 = 107.67$ ,  $df = 20$ ,  $CFI = 0.96$ ,  $AIC = 25836$ ,  $E_a = 0.08$ ).

Both poor and never poor families experienced gains and losses in income over time (see Table 3 for parameter estimates and Figure 3 as an exemplary illustration). Correspondingly, income showed significant variability in intercept and slope parameters in both groups, indicating change and variability in change was evident despite high cross-time correlations.

As previously documented, poor children had substantially lower average starting points and cognitive growth slopes in verbal comprehension and math ability throughout later childhood (see Table 3 for parameter estimates and Figure 4 for between-person comparison). Specifically, median group performance of poor children averaged 0.91 SD below never poor children for verbal comprehension and 0.96 SD for math ability. Furthermore, cognition showed significant variability in intercept and slope parameters in both groups, indicating change and variability in change. Thus, an investigation of bivariate dynamics was deemed feasible.

Table 3

*Univariate model parameter estimates for poor and never poor groups.*

	Income		Picture vocabulary		Math ability	
	Poor Estimate (SE)	Never poor Estimate (SE)	Poor Estimate (SE)	Never poor Estimate (SE)	Poor Estimate (SE)	Never poor Estimate (SE)
Intercept mean I	-1.77* (0.17)	0.20* (0.04)	-0.84* (0.13)	-0.04 (0.05)	-0.97* (0.12)	-0.05 (0.05)
Intercept variance $\sigma_I$	0.87* (0.06)	0.76* (0.03)	0.95* (0.03)	0.80* (0.03)	0.98 (0.02)	0.83* (0.03)
Proportional change $\beta$	-0.30* (0.06)	-0.30* (0.06)	-1.24* (0.30)	-1.30* (0.12)	-1.55* (0.53)	-1.26* (0.08)
Slope mean S	-0.02 (0.19)	1.66 (0.34*)	3.97* (0.26)	6.07* (0.25)	6.35* (0.41)	10.82* (0.43)
Slope variance $\sigma_S$	0.95* (0.02)	0.75* (0.06)	0.95* (0.03)	0.87* (0.03)	0.93* (0.04)	0.91* (0.02)
Covariance $\rho_{IS}$	-0.23 (0.15)	0.56* (0.08)	0.80* (0.12)	0.62* (0.07)	0.86* (0.12)	0.59* (0.07)
Gender <sup>a</sup> onto Intercept I	Fixed at 0	Fixed at 0	-0.24* (0.08)	-0.22* (0.07)	0.23* (0.08)	0.21* (0.07)
Gender <sup>a</sup> onto Slope $\eta_S$	Fixed at 0	Fixed at 0	-0.07 (0.05)	-0.09 (0.07)	-0.14* (0.05)	-0.22* (0.08)
Education <sup>b</sup> onto Intercept $\iota_I$	5.09* (1.04)	5.88* (0.30)	2.73* (1.17)	5.24* (0.41)	1.33 (1.3)	4.70* (0.41)
Education <sup>b</sup> onto Slope $\iota_S$	3.24* (0.61)	5.98* (0.75)	3.27* (1.01)	4.25* (0.44)	3.70* (0.99)	3.33* (0.45)

\*denote  $\Delta\chi^2$  significant at  $\alpha = 0.05$  comparing the standardized parameter freed versus fixed to 0 ( $\Delta df = 1$ ).

<sup>a</sup> Gender effect coded as -0.5 = male and 0.5 = female.

<sup>b</sup> Median maternal education was less than high school graduate for poor children and some college for never poor children.

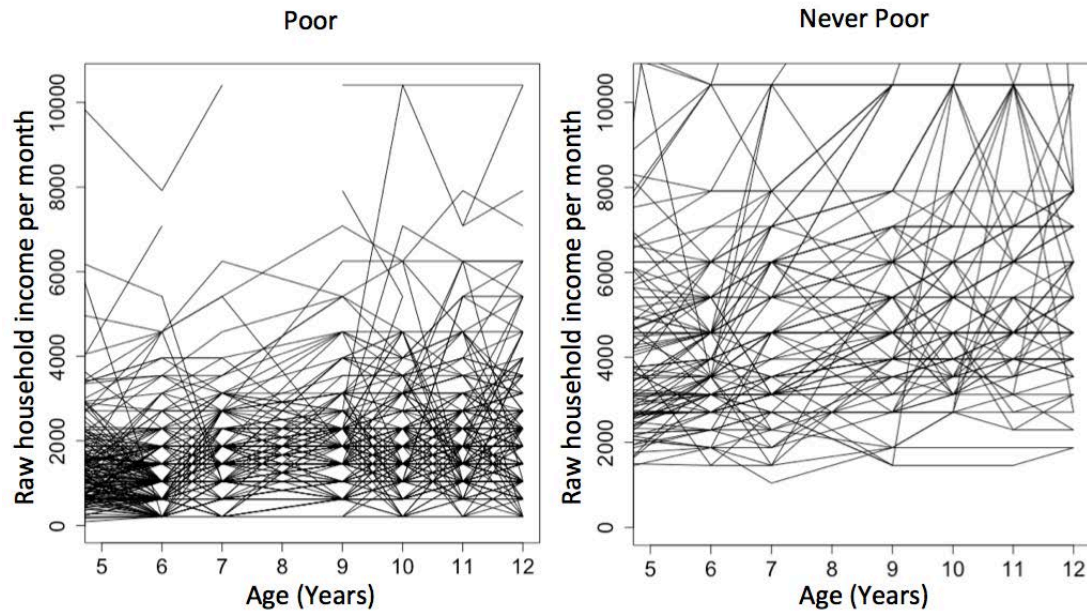


Figure 3. Individual raw monthly pre-tax income over time plotted for families living below the poverty threshold in at least one wave (poor, left panel) or never living below the poverty threshold in that period (never poor, right panel). Note that only 200 cases of never poor families are depicted to aid readability and some never poor families had monthly earnings considerably higher than 10 000 dollars, which is not shown to allow equal scaling of the y-axis. The figure exemplifies within-person gains and losses in income over time.

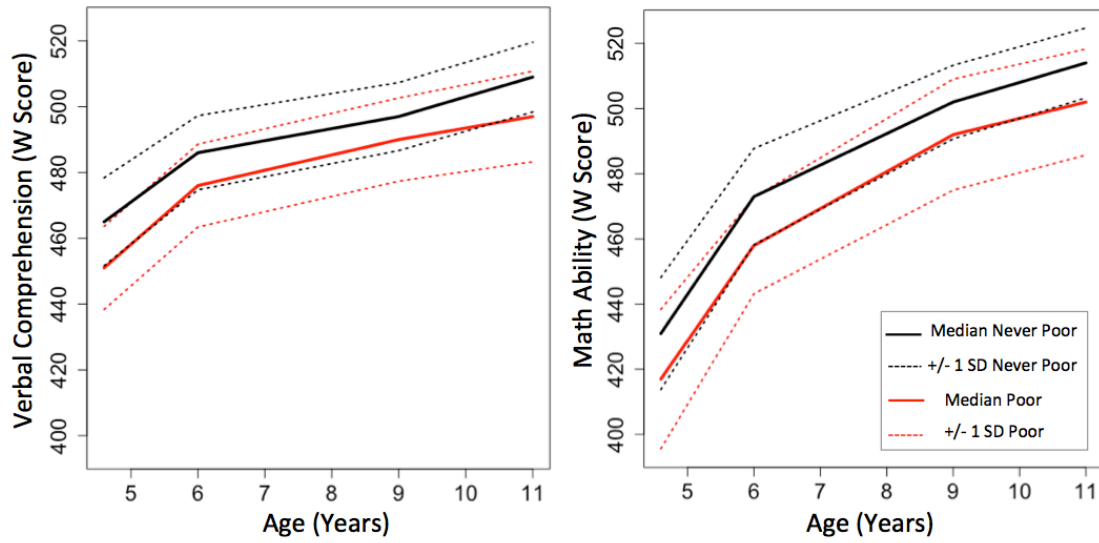


Figure 4. Median verbal comprehension (left panel) and math ability (right panel) scores for poor (red line) and never poor (black line) groups and  $\pm 1$  SD from the median of that group (dashed lines). This figure plots between-person cognitive differences across time.

**Aim 1: Bivariate score-onto-change dynamics**

The final model of income and verbal comprehension with bivariate covariances and score-onto-change coupling indicated good fit ( $\chi^2 = 339.79$ ,  $df = 146$ ,  $CFI = 0.98$ ,  $AIC = 67639$ ,  $E_a = 0.05$ , see Supplemental Material Table S1 for full model parameters). Concerning aim 1, income scores did not significantly predict verbal comprehension changes in middle childhood and early adolescence (see Table 4). Interestingly, verbal comprehension scores significantly and positively predicted income changes. This indicates that lower verbal comprehension scores (compared to other children) was a leading indicator in time of less increases in income (or higher scores predicting gains).

Bivariate models of income and math ability largely replicated these results ( $\chi^2 = 406.77$ ,  $df = 145$ ,  $CFI = 0.97$ ,  $AIC = 66806$ ,  $E_a = 0.06$ , see Supplemental Material Table S1 for full model parameters). Again, income scores did not significantly predict math ability changes in middle childhood and early adolescence (see Table 4). In reverse, math ability scores significantly and positively predicted income changes, but only for children that were never poor. Thus, lower math ability scores (compared to other children) was a leading indicator in time of less increase in income, but only for never poor families (or higher scores predicting gains).

Table 4. Bivariate score-onto-change coupling parameters between income and each cognitive domain

	Verbal comprehension		Math ability	
	Poor Estimate (SE) $\Delta\chi^2$	Never Poor Estimate (SE) $\Delta\chi^2$	Poor Estimate (SE) $\Delta\chi^2$	Never Poor Estimate (SE) $\Delta\chi^2$
Income score onto cognition change $\gamma$	0.00 (0.14) $\Delta\chi^2$ 0.07	-0.03 (0.16) $\Delta\chi^2$ 0.04	0.13 (0.10) $\Delta\chi^2$ 1.60	-0.05 (0.12) $\Delta\chi^2$ 0.15
Cognition score onto income change $\zeta$	0.07 (0.02) $\Delta\chi^2$ 3.93* <sup>a</sup>	0.07 (0.02) $\Delta\chi^2$ 3.93* <sup>a</sup>	0.05 (0.03) $\Delta\chi^2$ 3.35	0.05* (0.02) $\Delta\chi^2$ 4.05*

\* denote  $\Delta\chi^2$  significant at  $\alpha = 0.05$  comparing the standardized parameter freed versus fixed to 0 ( $\Delta df = 1$ ).

<sup>a</sup> The paths from VC cognition score  $\rightarrow$  income change were nonsignificant trends when unconstrained across groups that were significant when constrained to be the same across groups.

**Aim 2: Bivariate change-onto-score dynamics**

The final model of income and verbal comprehension with *change-onto-score* coupling indicated good fit ( $\chi^2 = 336.75$ ,  $df = 142$ ,  $CFI = 0.98$ ,  $AIC = 67644$ ,  $E_a = 0.05$ , see Supplemental Material Table S2 for full model parameters). Concerning aim 2, income changes significantly predicted verbal comprehension scores in middle childhood and early adolescence for poor children, but not for never poor children (see Table 5). In reverse, verbal comprehension changes did not predict income scores. Bivariate models of income and math ability replicated these results ( $\chi^2 = 408.64$ ,  $df = 144$ ,  $CFI = 0.97$ ,  $AIC = 66810$ ,  $E_a = 0.05$ , see Table 5 and Supplemental Material Table S2 for full model parameters). This indicates that higher income gains from one wave to the next was a leading indicator in time of higher verbal comprehension and math ability scores at the next wave for children living in poverty (or losses predicting lower scores). In contrast, income changes do not predict cognitive performance for children never living in poverty in middle childhood and early adolescence.



Table 5 Bivariate change-onto-score coupling parameters between income and each cognitive domain

	Verbal comprehension		Math ability	
	Poor Estimate (SE)	Never Poor Estimate (SE)	Poor Estimate (SE)	Never Poor Estimate (SE)
Income change onto cognition score $\kappa$	0.20 (0.08) $\Delta\chi^2$ 5.92*	0.01 (0.02) $\Delta\chi^2$ 0.22	0.12 (0.06) $\Delta\chi^2$ 4.54*	-0.01 (0.02) $\Delta\chi^2$ 0
Cognition change onto income score $\theta$	-0.01 (0.02) $\Delta\chi^2$ 0.17	0.00 (0.01) $\Delta\chi^2$ 0.31	-0.02 (0.02) $\Delta\chi^2$ 0.91	-0.01 (0.01) $\Delta\chi^2$ 0

\* denote  $\Delta\chi^2$  significant at  $\alpha = 0.05$  comparing the standardized parameter freed versus fixed to 0 ( $\Delta df = 1$ ).

### Discussion

This study showed that parental income change continues to be a leading indicator in time of both verbal comprehension and math ability performance throughout middle childhood and early adolescence for children experiencing poverty in this time span, but not for children never experiencing poverty in this period. Remarkably, lower child cognitive scores also predicted less income gains for both poor and never poor groups. This study emphasizes the need to look at the effects of changes in income and to further explore bidirectional dynamics between family income and children's cognition.

We extend previous research using family income or other SES indicators as static predictors of child outcomes, inferring the effects of income from between-person comparisons (Crosnoe et al., 2010; Lawson & Farah, 2017; von Stumm & Plomin, 2015; Wang et al., 2017). It shows that the positive effect of income changes predicting child cognition in early childhood (Dearing et al., 2001; Mistry et al., 2004) continues into later childhood and early adolescence for poor children. Our findings highlight the importance of exploring income dynamics in later childhood, because income *changes* predicted cognitive performance for poor children. Since this was consistent for verbal comprehension and math ability, we postulate that in general cognitive performance of poor children in later childhood is positively predicted by income gains and negatively predicted by income losses. Although these income changes in later childhood are unlikely to reorder between-person differences (Tucker-Drob & Briley, 2014) and poor children continued to have cognitive growth trajectories substantially lower than never poor children, our finding suggests that income fluctuations in poor families are still a leading indicator in time of cognitive performance.

We speculate that a multitude of proximal factors could mediate higher cognitive performance in poor children following family income gains or lower cognitive growth following losses, since income does not impinge directly on cognition. Previous studies have provided evidence that family-level environmental factors, such as material goods, parent stress, parent investment, and positive parenting behavior, are cross-sectionally associated with both SES and cognition (Gershoff, Aber, Raver, & Lennon, 2007; Mistry et al., 2004), or longitudinally mediate SES disparities in child executive function in part (Hackman et al., 2015). Importantly, the present study suggests that income gains versus losses also need to be considered as predictors of children's cognitive performance in later childhood. Indeed, cognitive stimulation in the home environment varies with changes in family income, particularly in low-income households (Votruba-Drzal, 2003). Following income increases, poor parents may be able to purchase relatively better educational materials at home, better quality activities, and more nutritious foods (Duncan et al., 2017). The family may also experience a reduction in stress by feeling some relief from financial strain and safer neighborhoods that has positive consequences for children's development (Morrison Gutman, McLoyd, & Tokoyawa, 2005; Raver, Roy, & Pressler, 2015). Alternatively, an omitted variable, such as improving maternal mental health, could influence both income gains and parenting practices that facilitate children's cognitive performance (McLoyd, 1990). Our study focused on identifying less biased, direct effects of income changes in later childhood, controlling stable effects of maternal education on growth slopes, rather than family-level characteristics, because they provide a lower bound estimate of income's effects that are of interest to public policy (Votruba-Drzal, 2003). Future research should continue to explore how income gains compared to losses are related to cognitive

development in poor children, preferably in intervention settings that allow for stronger causal inferences to be made.

In contrast, income did not predict children's cognitive development that were never poor in later childhood, which mirrors results on this sample in early childhood (Dearing et al., 2001). Although cognitive functioning and neural structure are associated with SES across the whole SES continuum in a gradient manner, the gradient seems to be steeper at the lower end (Hair, Hanson, Wolfe, & Pollak, 2015; Noble et al., 2015). This study provides further evidence for distinguishing interpretations based on the analysis of poverty compared to broad SES ranges, which may reflect differently weighted combinations of causes operating at different levels of disadvantage (Farah, 2017).

Genetically informed research suggests that cognition (Engelhardt, Briley, Mann, Harden, & Tucker-Drob, 2015), SES (Selzam et al., 2017) as well as their correlation are genetically influenced to a substantial degree (Ericsson et al., 2017; Krapohl & Plomin, 2016; Spinath & Bleidorn, 2017) and that genetic effects on cognition, especially after middle childhood, are substantially larger than environmental effects (Briley & Tucker-Drob, 2013; Ericsson et al., 2017; Tucker-Drob & Briley, 2014). Therefore, SES-cognition correlations across the SES gradient are at least partly explained by genetic effects. It is less clear, but not implausible, how genetic effects would account for cross-lagged income-to-cognition couplings we find in poor children. Behavior genetic studies suggest that genes explain more of the variance in cognition and brain structure in high-SES individuals than in low-SES individuals (Chiang et al., 2011; Tucker-Drob & Bates, 2016; Tucker-Drob & Harden, 2012b; Turkheimer, Haley, Waldron, D'Onofrio, & Gottesman, 2003), particularly in the US. In low SES, cognitive ability is almost entirely predicted by environmental

factors, whereas high-SES environments facilitate children to select learning experiences that better match their genetically influenced individual differences in interest (Tucker-Drob & Harden, 2012b). This implies that low-SES environments may suppress gene expression on child cognition. In contrast, enriched environments allow for more dissimilarity in the experiences organisms make within the same environment, even when they are genetically identical (Freund et al., 2013). We speculate that an SES x gene interaction could partially explain our findings, such that the SES-cognition correlation in never poor children derives more strongly from genetic effects, whereas income-related environments may influence poor children's cognition.

This is the first study to also explore bidirectional dynamics testing for reverse effects of child cognition on parental income. Interestingly, we found that when children's cognitive performance was lower than their developmental trajectory would predict, their parents made less income gains or made losses from that wave to the next. The proximal mechanism that may underlie this effect remains to be elucidated. However, based on the existing literature, we speculate that a plausible mechanism is that children with lower cognitive performance than other children may draw more investments from parents, potentially also affecting their psychological well-being (Miner & Clarke-Stewart, 2008), which in turn lowers income increases (McLoyd, 1990). Findings suggest that parents' feeling that their children are doing well is a strong indicator of self-reported work-family balance (Milkie, Kendig, Nomaguchi, & Denny, 2010) and especially mothers continue to reduce paid work to meet child rearing demands (Bianchi, 2011). Although this reverse effect of cognition on income was present for poor and never poor children's verbal comprehension, it was only significant for never poor children's math ability. Therefore, it may be a

stronger effect in more affluent families, who are better able to adjust their work investment depending on their children's needs (Lareau & Weininger, 2008). Deficits in verbal comprehension may be more noticeable to parents than math ability. Thus, lower child cognition may lead parents, especially mothers, to increase their investment in children at the cost of their career investment, thereby reducing family income gains. Again, including maternal education as a covariate allowed us to examine income-cognition coupling effects whilst accounting for stable income slope differences along gradients of maternal education. More generally, these bidirectional dynamics highlight that children are not merely the product of their environment and there are evocative and transactional mechanisms at play in family dynamics that link SES and child development.

As previously stated, an omitted variable, such as improving maternal mental health or shared genetic profiles, could affect parenting practices that influence children's cognitive performance and parents' future income changes (McLoyd, 1990). Future longitudinal studies should collect multiple SES indicators and associated constructs at each assessment, including parental investment to family versus career, cognitive stimulation, and psychological health to disentangle longitudinal mediation effects. They should make the substantial effort to over-sample at the lowest levels of social inequality strata to disentangle effects of SES and poverty and attempt to replicate this novel effect of children's cognitive state on family income changes. Exploring bidirectional coupling dynamics following exogenous income interventions would also present a powerful tool to explore long-term causal effects.

Several limitations of this study warrant attention. Firstly, the NICHD SECCYD sample is predominantly middle class and underrepresents severely

financially strained families. Although variation in income across time was significant, the average change in income was limited. Therefore, it is plausible that stronger effects of income changes in never poor groups or effects of income scores may be found in more disadvantaged samples with stronger income fluctuations. Strict exclusion criteria (such as health, maltreatment) are likely to have underestimated income effects, as these are somewhat more common at lower SES (Bradley & Corwyn, 2002; Evans & Kim, 2010; Häuser, Schmutzer, Brähler, & Glaesmer, 2011). Second, it is important to recall that income effects have been found to be most pronounced in early childhood (Duncan et al., 1998; Heckman, 2006), which was not measured here. While the gap in longitudinally measured cognition between higher and lower SES seems to be stable in older children as reported here and in Hackman et al. (2014), it greatly increases in early childhood (von Stumm & Plomin, 2015). The large between-person differences between poor and never poor groups may derive from disadvantage in poor children's early childhood environments (Tucker-Drob & Briley, 2014). Third, this study focused solely on cognitive outcomes. Positive long-term life outcomes, like adult salaries, and outcomes in noncognitive domains (e.g. school achievement) have been found even when no cognitive benefits were recorded following interventions (Heckman, 2006). Therefore, it is conceivable that income changes, which were not a leading indicator of cognition in never poor children, had a lead-lag relationship in noncognitive domains.

Fourth, longitudinal time-lagged coupling greatly strengthen our ability to test causal assumptions, but the analyses do not provide a direct test of causality. We can argue that we adequately represent the data in our models; however, we cannot claim that one model is a more valid representation of the world than another. Nevertheless,

representing longitudinal assessments of change in each variable as an outcome of the other variable's prior score or vice versa permits more evidence for causality than a large proportion of previous cross-sectional and longitudinal work. As previously mentioned, a proportion of our findings are also likely to be driven by genetic effects, specifically transactional mechanisms involving gene-environment correlation (Plomin, DeFries, & Loehlin, 1977). Future studies are needed to examine bidirectional income-cognition effects in consideration of gene-related factors.

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