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Creating a Developmental Scale to Chart the Development of Psychopathology With Different Informants and Measures Across Time

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Research Domain Criteria (RDoC) aims to advance a dimensional, multilevel understanding of psychopathology across the life span. Two key challenges exist in applying a developmental perspective to RDoC: First, the most accurate informants for assessing a person's psychopathology often differ across development (e.g., parents and teachers may be better informants of a person's externalizing problems in early childhood, whereas peer- and self-report may also be important to assess in adolescence). Second, many constructs change in their behavioral manifestation across development (i.e., heterotypic continuity). Thus, different informants and measures across time may be necessary to account for the construct's changing manifestation. The challenge of using different informants and measures of a construct across time is ensuring that the same construct is assessed in a comparable way across development. Vertical scaling creates a developmental scale to link scores from changing informants and measures to account for heterotypic continuity and study people's development of psychopathology across the life span. This is the first study that created a developmental scale to assess people's development by putting different informants and measures on the same scale. We examined the development of externalizing problems from ages 2 to 15 years (N = 1,364) using annual ratings by mothers, fathers, teachers, other caregivers, and self-report. The developmental scale linked different informants and measures on the same scale. This allowed us to chart people's growth trajectories and to identify multilevel risk factors, including poor verbal comprehension. Creating a developmental scale may be crucial to advance RDoC's goal of studying the development of psychopathology across the life span.

General Scientific Summary
This study linked different measures and informants to chart children's development of externalizing problems from ages 2 to 15 years. Poor verbal comprehension in very early childhood predicted later externalizing problems in adolescence. Linking measures and informants may be crucial to study development across the life span.

Keywords: heterotypic continuity, changing measures, externalizing problems, longitudinal, construct validity invariance

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Externalizing behavior problems, which consist of acting-out behaviors such as aggression, defiance, and conduct problems, are frequent, costly, and burdensome for individuals, families, and society. The worldwide prevalence of externalizing disorders (e.g., conduct disorder and oppositional defiant disorder) among children and adolescents is greater than 5% (Polanczyk et al., 2015). Therefore, it is important to advance understanding of how externalizing problems develop to enable design of more effective interventions.

The Research Domain Criteria (RDoC) from the National Institute of Mental Health provide a framework to advance a dimensional, multilevel understanding of psychopathology across the life

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A data dictionary of the study variables and scripts we used for vertical scaling are published at: https://osf.io/9zd6e. We have no conflicts of interest to disclose.

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span. A developmental approach to RDoC might examine the development of an underlying, trans-diagnostic dimension or mechanism of psychopathology, and relate it to potential etiological factors and the development of psychopathology constructs. For example, research could examine biobehavioral etiological factors in the development of inhibitory control and relate impaired growth in inhibitory control to the development of externalizing psychopathology. Inhibitory control, which is related to cognitive control in the RDoC matrix, is the ability to inhibit prepotent responses, and is considered an underlying phenotype of externalizing psychopathology (Young et al., 2009). However, key challenges exist in applying a developmental perspective to RDoC. Many RDoC constructs likely change in their manifestation across development (i.e., heterotypic continuity). For example, inhibitory control appears to demonstrate heterotypic continuity such that perceptual aspects of inhibitory control appear to develop before other cognitive, behavioral, and motivational aspects of inhibitory control (Petersen, Hoyniak, et al., 2016). Negative valence systems, including fear and anxiety are also involved in externalizing psychopathology (Mikolajewski et al., 2013) and show heterotypic continuity. Separation anxiety and animal fears are common in early childhood, whereas generalized anxiety and fears about danger and death are common in later childhood, and social anxiety is common in adolescence (Weems, 2008). Externalizing psychopathology also shows heterotypic continuity. In early childhood, externalizing problems often present in overt forms (e.g., temper tantrums), whereas in adolescence and adulthood, externalizing problems tend to present in covert or indirect forms (e.g., substance use; Miller et al., 2009).

Given heterotypic continuity, assessing the development of inhibitory control as an underlying phenotype of externalizing psychopathology across a lengthy developmental span would involve different measures across time to maintain developmental relevance. However, to our knowledge, no studies have examined growth in inhibitory control or other RDoC constructs with different measures over time to account for heterotypic continuity, and measures of inhibitory control are not available across the full age span of the sample in the present study (National Institute of Child Health and Human Development [NICHD] Study of Early Child Care and Youth Development [SECCYD]). The present study sought to provide an example of how to measure and link different measures (and informants) across development to account for heterotypic continuity, using an approach that could extend to RDoC constructs, by examining predictors of the development of externalizing psychopathology across a lengthy developmental span.

A second challenge in applying a developmental perspective to RDoC is that the most accurate informants often differ across development. For example, parents and teachers may be important informants of a person's externalizing problems in early childhood (De Los Reyes & Kazdin, 2005). In adolescence, however, it may also be important to assess peer- and self-report (Achenbach et al., 1987). Thus, different informants and measures across time may be necessary to account for the construct's changing manifestation. Use of different informants at different ages is further complicated by using different measures for different informants, given that different informants might be better for assessing some aspects of a behavior than others. For example, teachers may be better able to assess children's inhibitory control or externalizing problems in the school context, whereas parents may be better able to assess them in the home. The challenge of using different informants and measures of a construct across time is ensuring that the same construct is assessed in a comparable way across development.

Devising ways to use all available information to get the best estimate of a person's growth trajectory across the life span will be crucial for addressing key challenges of applying a developmental perspective to RDoC. First, doing so will allow incorporating multiple perspectives of the person's behavior even if different measures are used and not all informants are available at all ages. Second, it will allow building a bridge that spans childhood to adulthood, so we can advance understanding of how externalizing problems develop across the life span and across multiple levels of analysis (i.e., the RDoC matrix).

Heterotypic Continuity

Heterotypic continuity refers to the persistence of an underlying construct with behavioral manifestations that change across development (Cicchetti & Rogosch, 2002). Many RDoC constructs (e.g., inhibitory control, negative valence systems) likely demonstrate heterotypic continuity. Heterotypic continuity poses challenges for measurement because it necessitates using different measures across ages to maintain developmental relevance. If the RDoC construct changes in its manifestation over time and the measures do not accommodate these changes, the measures lack validity for the same construct across time, which may lead to faulty developmental inferences (Chen & Jaffee, 2015; Petersen et al., in press; Petersen et al., 2018). Moreover, using only the items that are in common across all ages would lack content validity because doing so would discard items that are important for assessing age-specific manifestations of the construct, which are often important for assessing clinical levels of the construct. For example, a measure that intends to assess the development of the negative valence system would lack content validity if the measure in early childhood discards content that assesses separation anxiety, even though separation anxiety is less developmentally relevant in later childhood. The loss of developmentally relevant items would also result in a loss of information that makes measures less able to detect developmental change (Petersen et al., 2018). Thus, different measures over time may be necessary to capture people's growth in RDoC constructs that show heterotypic continuity. In sum, accounting for heterotypic continuity is crucial to advance the RDoC goal to understand how biobehavioral processes develop and how they lead to the emergence of psychopathology.

Despite a proliferation of studies demonstrating that many constructs show heterotypic continuity, surprisingly little research has considered how to examine people's developmental trajectories in constructs that change in manifestation over time (i.e., how to account for heterotypic continuity when examining development). Few studies have examined people's growth across development using different, age-appropriate measures across time to maintain construct validity when the construct shows heterotypic continuity. Very few studies have examined trajectories in ways that account for heterotypic continuity by using different measures across time (Petscher et al., 2018), and even fewer have done so in ways that allow researchers to examine absolute change (McArdle et al., 2009; Petersen & LeBeau, in press; Petersen et al., 2018). And no

studies, to our knowledge, have done so while incorporating different informants across ages.

Accounting for Heterotypic Continuity in Development

There have been many attempts to ensure statistical equivalence of scores from different measures across time. One approach that has been used is the age-norming approach such as *z*- or *T* scores (Cherlin et al., 1998). However, age-norming fixes the mean and variance across ages to be equal, so it does not meet our goal to examine people's absolute growth across the life span. Another approach used in prior research is average (Owens & Shaw, 2003) or proportion (Petersen, Bates, Dodge, et al., 2015) scores that account for the different numbers of items in each measure. However, average and proportion scores have strong assumptions that the items on each measure reflect the same severity of externalizing problems, which is unlikely in the present study because externalizing problem items likely change in severity across childhood to adolescence. For example, an item asking how often a person "physically attacks people" would be expected to be more severe in adolescence compared to childhood.

To ensure statistical equivalence of scores from different measures, researchers recommend creating a developmental scale using vertical scaling (Kolen & Brennan, 2014). In the present study, we use an item response theory (IRT) approach to vertical scaling. The IRT approach to vertical scaling yields more accurate developmental inferences than traditional measurement approaches that ignore heterotypic continuity (Petersen et al., in press) and thus holds great potential to model development of RDoC constructs. IRT estimates two parameters for each item: discrimination and severity (difficulty). An item's discrimination parameter describes how well the item distinguishes between low and high levels of the construct. For example, because an item asking how often a child attacks people is more relevant to externalizing problems than an item asking how often a child brags, "attacks people" has a higher discrimination parameter for externalizing problems than "brags" (Petersen, Bates, et al., 2016). An item's severity parameter describes the construct level at which the probability of endorsing the item is 50%. For example, if a child sets fires, the child is likely to be higher in externalizing problems than children who argue, because fire-setting occurs less frequently than arguing and is a more severe form of externalizing behavior (Petersen, Bates, et al., 2016). Thus, "sets fires" is more severe than "argues" for externalizing problems.

In vertical scaling, measures that assess the same construct but differ in severity or discrimination are placed on the same scale. The goal of vertical scaling is to assemble and link a construct-valid set of items at each age that have some overlap in items at adjacent ages (i.e., common items) on the same scale. Scores on the construct-valid items at the referent age set the scale, the common items adjust subsequent scores to that scale, and all construct-valid items (i.e., both common and unique items) at a given timepoint are used to estimate each person's score on that scale. Thus, the common items are used to determine the general form of change on an identical scale, but all developmentally relevant, construct-valid items are used to estimate each person's construct level on this scale. The IRT approach to vertical scaling involves scaling parameters that put people's construct scores from different measures on the same metric. The scaling parameters are determined as the linear transformation (i.e., intercept and slope parameter) that, when applied to the second measure, minimizes differences between the probability of a person endorsing the common items across two measures. That is, IRT links measures' scales based on the severity and discrimination of the common items.

The IRT approach is often used for vertical scaling, especially in cognitive and educational testing. For instance, McArdle and colleagues (2011, 2009) examined the development of cognitive ability from 2 to 72 years of age using different measures across time and an IRT approach to vertical scaling. The authors used developmentally appropriate, construct-valid items for vocabulary and memory span, and linked the different measures based on the difficulty of common items.

However, very few studies have used vertical scaling to examine social development (Petersen et al., 2018), and only one such study to our knowledge has examined the development of externalizing problems (Petersen & LeBeau, in press). No prior studies, to our knowledge, have used vertical scaling to account for heterotypic continuity when examining people's growth while incorporating multiple perspectives (informants). Considerable informant discrepancies are frequently observed (De Los Reyes & Kazdin, 2005). It can be challenging to determine the extent to which rater discrepancies reflect true construct differences (e.g., differences in a child's level of externalizing problems in the home vs. school context) versus reporter-specific bias versus measurement differences (e.g., differences in the functioning of a measure). Having multiple informants and putting different informants and measures on the same scale is thus crucial to account for the considerable informant discrepancies that are frequently observed and to derive the best possible estimates of people's trajectories.

The Present Study

The present study provides a demonstration of how to place different informants and measures on the same scale to advance understanding of the course and predictors of long-term development, using the example of externalizing problems, an approach that can be extended to RDoC constructs. We examined people's development of externalizing problems using (nearly) annual ratings from 2 to 15 years of age. To span the wide age range, we assembled different measures across time to maintain construct validity and developmental relevance for externalizing problems. We also examined multiple perspectives (informants) of the participants' externalizing behavior, including mothers, fathers, teachers, other caregivers, and self-report. This is the first study that created a developmental scale to assess people's development by putting different informants and measures across ages on the same scale. To create a developmental scale, we used IRT and vertical scaling. Then we examined people's growth trajectories to identify risk and protective factors that predicted the trajectories, including demographic factors, socioeconomic status (SES), and language ability. Language ability has been shown to predict the development of externalizing problems (Chow et al., 2018). However, it is not known whether language ability in very early childhood predicts the development of externalizing problems across the lengthy developmental span from early childhood to adolescence. Consistent with RDoC aims, we also examined theoretically relevant biobehavioral processes (blood pressure, cortisol, and physical

activity) to determine whether they may have unique contributions to externalizing problems.

Method

Participants

Children (N = 1,364; 659 girls and 611 first-born) and their families were recruited for the NICHD SECCYD study in 1991 from 31 hospitals near one of 10 locations in the United States: Little Rock, AR; Irvine, CA; Lawrence and Topeka, KS; Boston, MA; Charlottesville, VA; Morganton and Hickory, NC; Seattle, WA; and Madison, WI. Infants were recruited at birth and were followed until they were 15 years old. Although the sample is not nationally representative, it reflects a diverse sample. In terms of the child's ethnicity, the sample was 80.4% White, 12.9% Black, 1.6% Asian American, 0.4% American Indian, and 4.7% of "other" ethnicity. Of children, 6.1% were Hispanic. At intake, mothers ranged from 18 to 46 years of age (M = 28.11, SD = 5.63). Households had 4.27 people on average (SD = 1.17), and 77% had fathers living in the home. For more information about the study and sampling procedures, see the NICHD Early Child Care Research Network (2005).

Measures

A data dictionary of the study variables and scripts we used for vertical scaling are published at https://osf.io/9zd6e. A correlation matrix of model variables and their descriptive statistics (including percent missingness) are in Supplementary Table S1 in the online supplemental material.

Externalizing Behavior Problems

The child's externalizing problems were rated by mothers, fathers, teachers, afterschool caregivers, other caregivers, and self-report. Table 1 depicts when each rater provided ratings of the child's externalizing problems. Mothers and/or fathers rated the child's externalizing problems on the Child Behavior Checklist 2–3 (CBCL 2–3; including the Aggressive Behavior and Destructive Behavior subscales; Achenbach, 1992) at ages 2–3 years and on the Child Behavior Checklist 4–18 (CBCL; including the Aggressive Behavior and Delinquent Behavior subscales; Achenbach, 1991a) at ages 4–6, 8–11, and 15 years. Teachers rated the child at ages 5–11 years on the Teacher's Report Form (including the Aggressive Behavior and Delinquent Behavior subscales; Achenbach, 1991b). Afterschool caregivers rated the child at ages 6 and 8–10 years on the CBCL 4–18. Other caregivers (e.g., preschool teacher, daycare provider, babysitter) rated the child at ages 2–3 years on the CBCL 2–3 and at age 4 years on the Caregiver–Teacher Report Form 2–5 (including the Aggressive Behavior and Attention Problems subscales; Achenbach, 1997). The participant self-rated their own externalizing problems at age 15 years on the Youth Self-Report (including the Aggressive Behavior and Delinquent Behavior subscales; Achenbach, 1991c). Items were rated as "not true," "somewhat or sometimes true," or "very true or often true," scored 0, 1, and 2, respectively. Supplementary Table S2 in the online supplemental material describes the number of items in each measure and the number of common items that each measure shares with each other. Although which items were common items differed between different pairs of measures, in general, items dealing with destructive behavior, aggression, getting into fights, and having a temper tended to be age- and rater-common items. Internal consistency estimates by age and rater are in Supplementary Table S3. The Achenbach scales are empirically derived, widely used, and the scores show strong reliability (internal consistency, test–retest reliability, and interrater reliability) and validity (content, construct, and criterion-related validity; Sattler, 2014).

Because of the wide age range spanned in the present study, we aimed to ensure we were assessing the same externalizing problems construct on the same scale across time. This is an important consideration because the present study used different informants (i.e., raters) and measures across time to account for the change in externalizing problems across development, often from overt to covert forms of behavior (i.e., heterotypic continuity; Chen & Jaffee, 2015; Petersen, Bates, Dodge, et al., 2015). To ensure we were assessing the same externalizing problems construct on the same scale across ages, we created a developmental scale by using an IRT approach to vertical scaling, consistent with recommendations from previous research (described later; Kolen & Brennan, 2014; Petersen et al., 2018). Vertically scaled IRT-derived factor scores were used as the child's level of externalizing problems, with higher levels corresponding to greater externalizing problems. Factor scores of externalizing problems at each age were scaled in reference to the factor scores of mothers' ratings of externalizing problems at age 6. Descriptive statistics of externalizing problems by age and rater are in Supplementary Table S4 in the online supplemental material. Factor scores of mothers' ratings of externalizing problems at age 6 had a mean of zero and a standard

Table 1
The Child's Age When Each Rater Provided Ratings of the Child's Externalizing Problems

	Age (years)											
Rater	2	3	4	5	6*	7	8	9	10	11	. . .	15
Mother*	x	x	x	x	x		x	x	x	x		x
Father					x		x	x	x	x		x
Teacher				x	x	x	x	x	x	x		
Afterschool caregiver					x		x	x	x			
Other caregiver	x	x	x									
Self-report												x

Note. "x" indicates the measure was collected at the specified age; "*" indicates the referent age and rater.

deviation near one. The percentage of participants with externalizing problems scores at different numbers of time points is presented in Supplementary Table S5. A correlation matrix of externalizing problem scores by rater is in Supplementary Table S6. The mean 1-year stability coefficients of externalizing problem ratings within rater are in Supplementary Appendix S1.

Predictors

In addition to the child's demographics (sex and ethnicity) as predictors of the child's externalizing problems, we also examined other predictors including SES (the family's income-to-needs ratio) and children's language ability. The family's income-to-needs ratio was assessed when the child was 1-month-old. The child's language ability was assessed at age 3 years using the Reynell Developmental Language Scales (Reynell, 1991), which is a performance-based measure that includes 67-item scales of the child's receptive and expressive language skills. Cronbach's alpha was .93 for verbal comprehension (receptive) and .86 for expressive language. We used standard scores for children's verbal comprehension and expressive language that were referenced to an age-normed population with a mean of 100 and standard deviation of 15, with higher scores reflecting better ability.

We also examined biobehavioral processes assessed at age 15, including blood pressure, cortisol, and physical activity, as correlates of externalizing problems. Blood pressure was operationalized as mean arterial pressure (mmHg) assessed by a blood pressure cuff during a lab visit. Cortisol (mcg/dl) was assessed by assay of saliva samples collected upon morning awakening. Physical activity was operationalized as average percent of time per day spent in moderate to vigorous activity as assessed by accelerometer. These biobehavioral processes were theoretically selected because of their potential roles in externalizing problems identified in prior work (described in Supplementary Appendix S2 in the online supplemental material). Thus, blood pressure, cortisol, and physical activity served as important covariates to inform potential biological mechanisms in externalizing problems. More details about the assessment of blood pressure, cortisol, and physical activity are in Supplementary Appendix S2.

Statistical Analysis

Developmental Scale of Externalizing Problems

We used IRT and linking (as described in Kolen & Brennan, 2014) to create a single uniform developmental scale for externalizing problems that spans multiple years of development. The approach fit an IRT model to the externalizing problems scale separately at each age (i.e., wave) and for each rater. After estimating item parameters, we then linked the item parameters onto a single uniform developmental scale across age and raters. Finally, we estimated the latent externalizing factor scores for each child at each age and rater on the same scale. We describe this procedure in detail below.

We used the graded response IRT model (Samejima, 1969) using the mirt package (Chalmers, 2012) in R 3.4.1 (R Core Team, 2019) to estimate item parameters. The mirt package uses a maximum likelihood expectation-maximization algorithm to estimate item parameters (Bock & Aitkin, 1981). The maximum likelihood estimation procedure uses all available data for each item and provides valid inferences if the data are missing at random or completely at random. The graded response model is a generalized version of the two-parameter logistic model for dichotomous outcomes, accommodating polytomous items that are ordinal in nature through a series of cumulative comparisons (de Ayala, 2009). The externalizing problem items in the current study were questionnaire items rated from 0 to 2. The graded response model takes the following general form:

$$P(X_{ni} = x_{ni}|\theta_n) = P^*_{x_{ni}}(\theta_n) - P^*_{x_{ni}+1}(\theta_n) \quad (1)$$

where

$$P^*_{x_{ni}}(\theta_n) = P(X_{ni} \geq x_{ni}|\theta_n) = \frac{1}{1 + e^{a_i(\theta_n \pm b_{ic})}}. \quad (2)$$

In this model, three parameters are of primary interest, a_i, which is an item-specific discrimination parameter; b_{ic}, which is an item-specific severity parameter (commonly referred to as difficulty in educational measurement literature); and θ_n, which is a subject-specific latent variable representing the child's level of externalizing problems. In the above model, i represents unique items, c represents different categories that are rated, and n represents unique children. Because the respondent rates each item from 0 to 2, there are two b_{ic} item-specific severity terms reflecting the category boundary locations. The category boundary locations reflect the point at which the probability of being in category c or lower compared to the categories above c is 50%. For example, if $b_{i1} = 1.2$, there is a 50% probability of being in category 0 or 1 (i.e., category c or lower) compared to category 2 (i.e., categories above c) at this value, 1.2, on the externalizing problems scale.

There may be shifts in the externalizing problems construct over time due to natural developmental changes (e.g., Petersen, Bates, Dodge, et al., 2015). Although these construct shifts are expected theoretically, the graded response model shown above assumes unidimensionality. When spanning a wide age range, it is considered safer to fit a separate model at each age rather than a single model that spans across all ages because a model that spans across all ages is more likely to violate the unidimensionality assumption of IRT (Kolen & Brennan, 2014). Thus, we fit a separate IRT model at each age and for each rater in the present study. This approach was also applied by Petersen et al. (2018) and by Petersen and LeBeau (in press) in their creation of a developmental scale for internalizing and externalizing problems, respectively, across a wide age range. Our data were "unidimensional enough" for IRT (see tests of unidimensionality in Supplementary Appendix S3 in the online supplemental material). Tests of differential item functioning showed no major concerns and are in Supplementary Appendix S4.

After successful estimation of the IRT models, we used linking methodology to create the externalizing problems developmental scale (Kolen & Brennan, 2014). Details of our vertical scaling approach to linking measures' scores are in Supplementary Appendix S5 in the online supplemental material. Vertical scaling aims to place two measures that assess the same construct but differ based on severity and discrimination onto the same scale. One way to create a vertical scale is to link the two measures. The strength of the linking is enhanced if there are items that overlap across the two measures, often referred to as common items or anchor items in educational measurement (Holland & Dorans,

2006; Kolen & Brennan, 2014). Because of item parameter invariance theory, any difference in item parameter estimates should be able to be rescaled onto a single unified metric with a linear transformation (Kolen & Brennan, 2014). The item parameters, and the resulting latent factor scores of externalizing problems can then be linked across ages by comparing and linearly transforming differences in discrimination and severity across the waves. We created the developmental scale by linking scores across ages and raters with four steps:

1. As described above, we fit IRT models at each wave and for each rater separately.

2. We used vertical scaling techniques to link the measure over time within each rater. We classified teachers and "other caregivers" as the same rater role for the purposes of linking because "other caregivers" often included preschool teachers and daycare providers. We used the plink package (Weeks, 2010) in R to perform the linking by using the Stocking-Lord (SL) procedure (Stocking & Lord, 1983). The SL is an iterative procedure that estimates linking constants by minimizing differences in the aggregate scores across common items. We used the SL linking procedure as opposed to other linking procedures (e.g., Haebara) because we were interested in construct-level (i.e., externalizing problems) scores and were less interested in the response to a single item. Nevertheless, there has been little empirical difference shown between the two characteristic curve linking methods, SL and Haebara (Hanson & Béguin, 2002; Kim & Lee, 2006; LeBeau, 2017).

   To estimate the SL parameters, we set the referent age at 6 years for each rater because age 6 was the first age when all raters (except self-report) provided ratings of the child's externalizing problems. We set the referent rater to be the mother because the mother typically provided the most ratings across the developmental age span. The referent age and rater pair set the scale to which the item parameters at subsequent ages and for other raters were transformed. In other words, we transformed the estimated item parameters at all ages and for all raters to be on the same scale as the item parameters estimated for mothers' ratings at 6 years of age. To achieve this, we first linked the item parameters across ages within rater. We performed the process of linking iteratively by chaining together multiple linking constants across the age span. First, for a given rater, we estimated SL linking constants that linked the item parameters at age 7 to be on the same scale as that rater's item parameters at age 6. We estimated additional linking constants between adjacent age spans, for example between 5 and 6 years of age, 7 and 8 years of age, and so on. We used two estimated scaling constants including an intercept parameter, B, and a slope parameter, A, to link the item parameters onto the reference scale.

   After successfully estimating the linking constants, we then transformed all item parameters to be on the age 6 scale for the given rater. The transformations took the following form:

$$\alpha(\text{age}_i) = \frac{\alpha(\text{age}_j)}{A}, \tag{3}$$

$$b(\text{age}_i)_c = A \times b(\text{age}_j)_c + B, \tag{4}$$

   where α (age_i) and α (age_j) are discrimination parameter estimates for the common items at adjacent ages i and j respectively; b (age_i)$_c$ and b (age_j)$_c$ are severity parameter estimates for the common items at adjacent ages i and j respectively for category c; A represents the slope scale parameter, and B represents the intercept scale parameter. To shift all item parameters to a common age 6 scale, we applied all previous adjacent scaling constants to the item parameters. For example, when shifting the item parameter estimates for 7-year-olds to the age 6 scale, we used a single set of scaling constants. However, when shifting the item parameters for 8-year-olds, we used two sets of scaling constants: first, we transformed the item parameter estimates for 8-year-olds to the scale of the 7-year-olds, and then we transformed them a second time to be on the age 6 scale. See Figure 1 for a visualization of the linking process. We performed this step of the linking process separately for each row in the figure (i.e., within raters; horizontal arrows).

3. After creating developmental scales across age within raters, we linked scores across raters at age 6 only (except for the self-report measure collected at age 15). As described above, we set the mother as the referent rater. We used a similar process as in Step 2; namely we estimated SL linking constants to link the item parameters across raters within a single age. For example, we estimated a set of linking constants to link the item parameters of the fathers' ratings to the item parameters of mothers' ratings at age 6 to ensure that their factor scores are on the same scale. This step moved the developmental scales for fathers, teachers, and afterschool caregivers to the mothers' scale, anchored at age 6, while preserving the developmental scale created within raters in Step 2. The process of linking scores across raters is depicted in Figure 1 with the gray bounding boxes (vertical arrows).

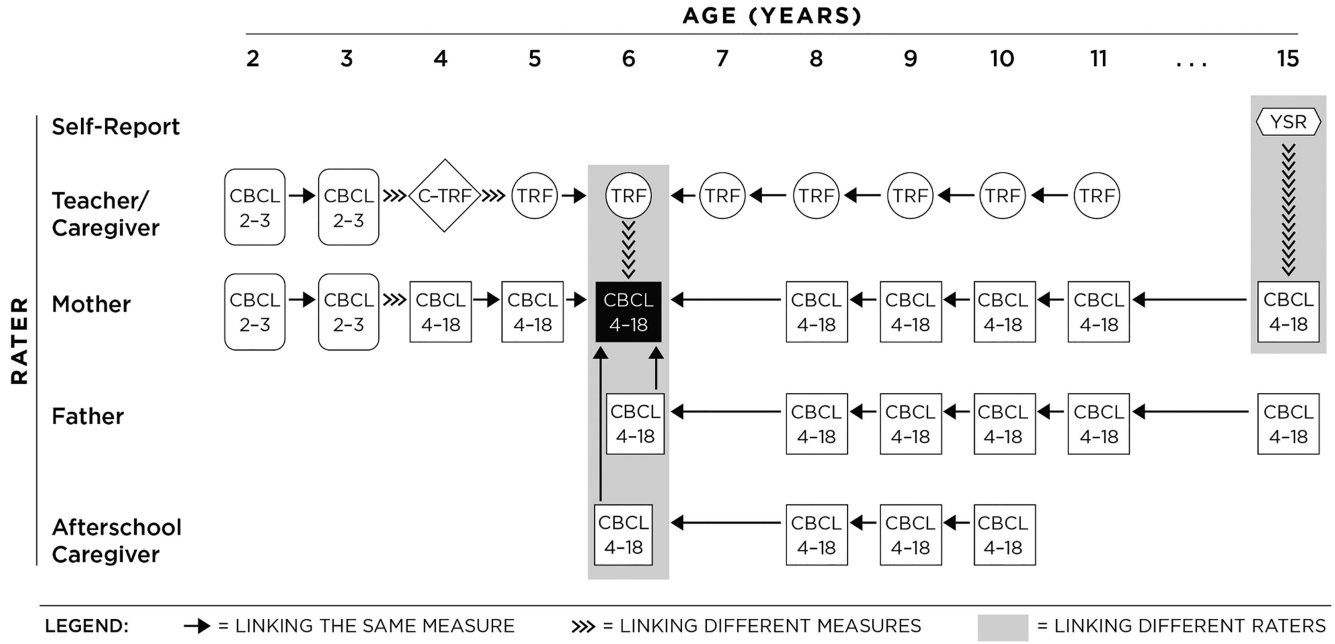
4. After successfully placing item parameter estimates on a single developmental vertical scale (for all raters and ages), we calculated children's latent externalizing problems scores with expected a posteriori factor scores (Thissen et al., 1995). The linking in the previous two steps scales the factor scores to be on the single developmental vertical scale while still retaining changes in means and variances over time and across raters. The factor scores are assumed to be linearly related based on the following equation:

$$\theta(\text{age } 6) = A \times \theta(\text{age}_j) + B \tag{5}$$

   where θ(age 6) represents the factor scores at age 6 (the referent scale) and $\theta(\text{age}_j)$ represents the factor scores at subsequent measurement occasions. The chaining de-

Figure 1

Depiction of How the Raters and Measures Were Linked at Different Ages



Note. Raters are depicted in the rows, and the child's age (in years) is depicted in the columns. Different shapes indicate different measures (square = Child Behavior Checklist 4–18; rounded square = Child Behavior Checklist 2–3; circle = Teacher's Report Form; diamond = Caregiver–Teacher Report Form; hexagon = Youth Self-Report). A solid arrow indicates that scores from the same measure were linked using all items (i.e., all items were common items; e.g., mothers' ratings at ages 6 and 8). A broken arrow indicates that scores from different measures were linked using the common items (e.g., mothers' ratings at ages 3 and 4). The direction of the arrow indicates the measure to which the other was linked (e.g., mothers' ratings at age 8 were linked to mothers' ratings at age 6). The solid black box indicates the referent measure (mothers' ratings at age 6) to which every other measure was linked either directly or indirectly. The gray bounding boxes indicate that scores from different raters were linked using the common items (e.g., self-report ratings at age 15 were linked to mothers' ratings at age 15). CBCL = Child Behavior Checklist; YSR = Youth Self-Report; TRF = Teacher's Report Form.

scription referenced with the linking applies here as well. For example, the factor scores at age 8 use two sets of linking constants to transform them to the age 6 referent age: one between ages 6 and 7 and another between ages 7 and 8. Finally, after creating the developmental scale within each rater, we then linked each rater to the age 6 mother scale using a similar equation to above, except now only a single transformation was used across each rater.

$$\theta(\text{age } 6_{mother}) = A \times \theta(\text{age } 6_{r}) + B \quad (6)$$

where $\theta(\text{age } 6_{\text{mother}})$ represents the factor scores at age 6 for the mother rater and $\theta(\text{age } 6_{r})$ represents the factor scores at age 6 for the *r* raters including fathers, teachers/caregivers, and afterschool caregivers. For transforming the self-reported scores at age 15 to mothers' ratings, we linked the scores with a similar equation, however we used the transformed mothers' ratings at age 15 as the referent group (see Figure 1). The linking constants by measure and age are in Supplementary Table S7 in the online supplemental material.

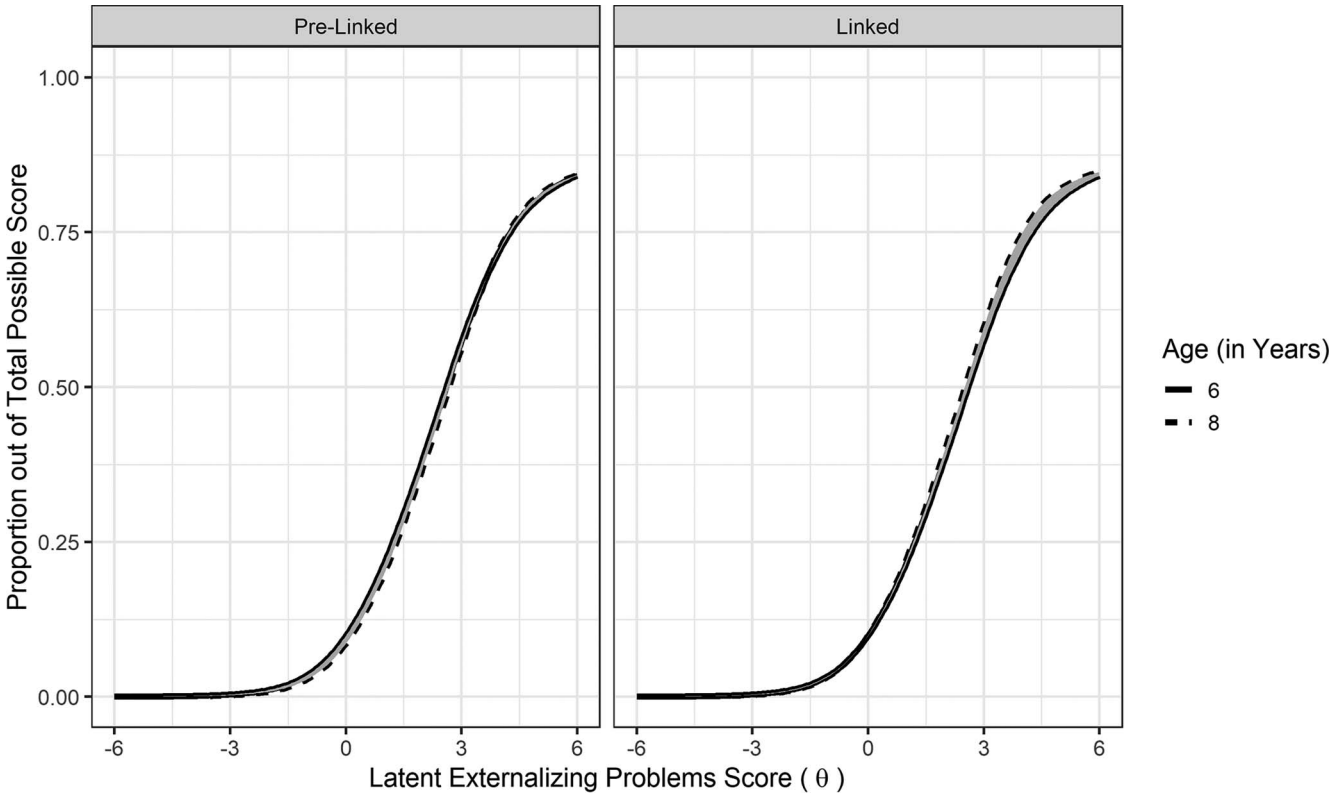
In sum, the linking of scores within a rater creates a developmental scale for scores from that rater, so each rater has their own trajectory. We then, ultimately, linked each rater's developmental scale (directly or indirectly) to the mother's ratings at age 6, so that each rater's trajectory is on the same developmental scale. Examples of linked scores across raters and years are depicted with test characteristic curves in Figures 2 through 4. The test characteristic curves of the linked scores across raters and years were highly similar (and more similar than the test characteristic curves of the prelinked scores), indicating that we successfully linked scores across raters and years to be on the same scale.

Modeling Externalizing Trajectories

We modeled externalizing problem trajectories using a linear mixed model (LMM). Because our goal was to predict externalizing problems in adolescence, we set the intercepts to be at the last time point (age 15), consistent with prior research (Owens & Shaw, 2003). First, we established the form of change (i.e., linear, quadratic, etc.) of people's externalizing problems over time using a model that included fixed effects for the time trajectory in years and the rater as a dummy coded attribute with mother as the referent group. We included random effects for the intercept and linear slope and conducted additional tests for a quadratic random effect. We used the bias-corrected Akaike information criterion as a means to establish the best fitting unconditional model, which

Figure 2

Test Characteristic Curves of Prelinked Compared to Linked Scores at Ages 6 and 8 for Mother-Rated Externalizing Problems



Note. The test characteristic curves of the linked scores were highly similar and more similar than the test characteristic curves of the prelinked scores, especially in the middle of the distribution (−2 to +2 standard deviations of the mean), where most scores reside.

established the baseline model to which models with focal predictors could be compared.

Upon establishing the form of the trajectory, demographic fixed effects were added to the model, including the child's sex, ethnicity (White, African American, and Hispanic were dummy-coded), and the family's income-to-needs ratio. We then added the focal predictors of interest, the child's verbal comprehension and expressive language ability. Because verbal comprehension and expressive language ability were highly correlated, we examined them in separate models. For parsimony and interpretability, we examined the predictors in relation to the intercepts and linear slopes. We then added the biobehavioral processes (blood pressure, cortisol, and physical activity) as predictors of the ending values of externalizing problems. Model formulas are in Supplementary Appendix S6 in the online supplemental material.

We determined the importance of focal predictors using R^2 statistics to evaluate how much variation in the externalizing problems are explained by the rater predictors, demographic predictors, and focal predictors of interest. We computed R^2 statistics defined by Nakagawa and Schielzeth (2013). In Supplementary Appendix S7 in the online supplemental material, we describe tests of systematic missingness and how missing data were handled.

Results

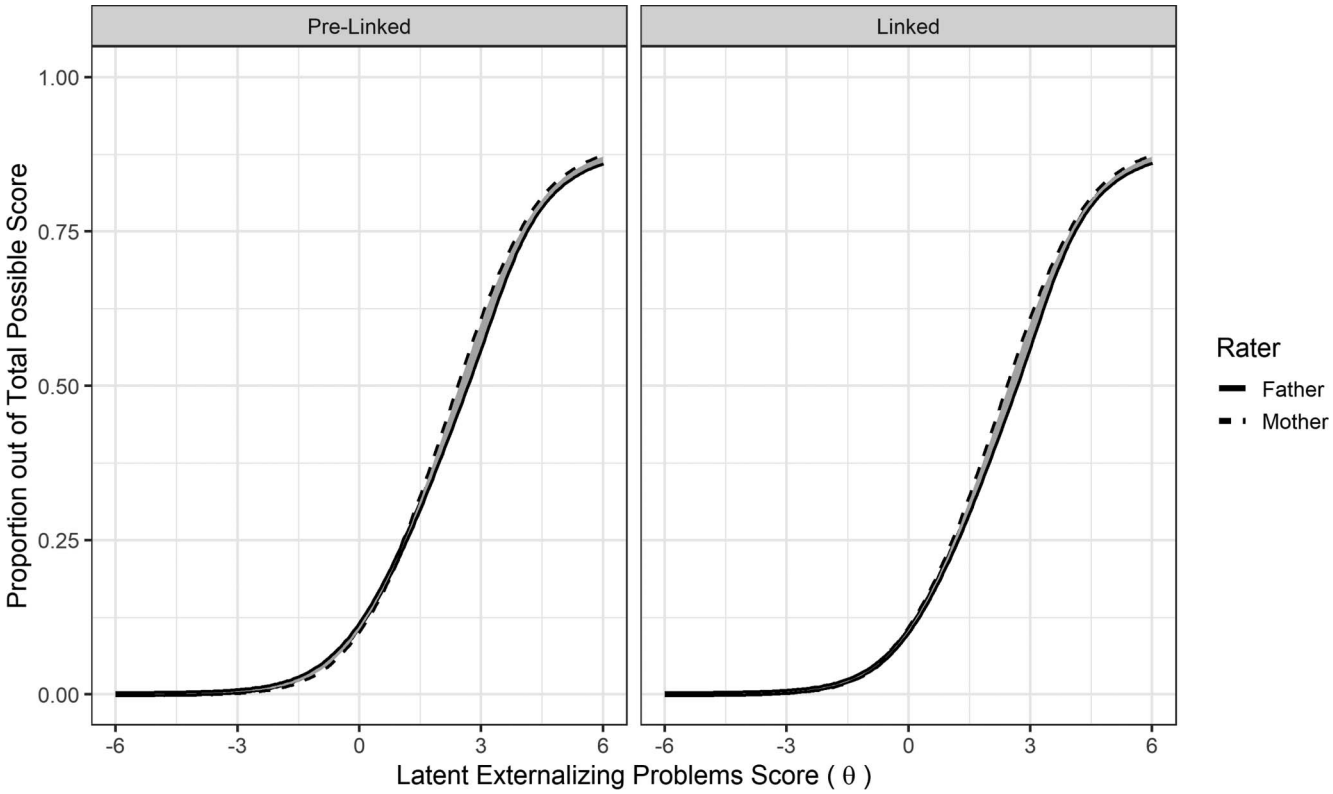
Form of Change

We fit four models to identify the best fitting form of change prior to adding other predictors. Nested model comparisons are in Supplementary Appendix S8 in the online supplemental material. The model with random linear and fixed quadratic slopes that varied by rater role was the best fitting model and was selected as the baseline model with which subsequent models were compared. Results from the baseline growth model that accounts for the effects of rater role are in Supplementary Table S10. This model had a marginal R^2 of .20, indicating that the fixed effects (i.e., linear, quadratic, and rater role variables) explained 20% of the variance in externalizing problems.

Examining trajectories of externalizing problems by rater role, we found that teachers and other caregivers rated children as showing lower levels of externalizing problems compared to ratings by mothers ($\beta = -0.16$; see Figure 5). Moreover, fathers rated children as having higher levels of externalizing problems compared to mothers' ratings at age 15 ($\beta = 0.01$). Furthermore, caregivers/teachers' ratings showed curvilinear growth curves (decreases from early to middle childhood and increases into adolescence). By contrast, mothers', fathers', and afterschool caregivers'

Figure 3

Test Characteristic Curves of Prelinked Compared to Linked Scores for Mother- and Father-Rated Externalizing Problems at Age 6



Note. The test characteristic curves of the linked scores were highly similar and more similar than the test characteristic curves of the prelinked scores, especially in the middle of the distribution (−2 to +2 standard deviations of the mean), where most scores reside.

ratings showed linear decreases. Self-report showed higher levels than mothers' ratings ($\beta = 0.17$) and showed the highest levels of all informants. Individuals' growth curves are depicted in Figure 6.

Predictors: Demographic Factors and SES

Results from the growth model that accounts for demographic and socioeconomic factors are in Supplementary Table S11 in the online supplemental material. African Americans (compared to Whites; $\beta = 0.08$) and children from families with a lower income-to-needs ratio ($\beta = -0.09$) showed higher levels of externalizing problems at age 15 (and age 2), but they showed no differences in slopes ($|\beta s| \leq .01$).

Predictors: Language Ability

Results from the growth model with language ability and covariates are in Supplementary Table S12 in the online supplemental material. Poorer verbal comprehension at age 3 was associated with higher initial levels of externalizing problems ($\beta = -0.13$), and the association was enduring such that children with poorer verbal comprehension continued to show higher externalizing problems when they were 15 (see Figure 7). Poorer expressive language skills at age 3 were associated with higher initial levels of externalizing problems. However, children with poorer expressive language skills tended to show greater decreases in externalizing problems over time and showed no significant differences in externalizing problems at age 15 (compared to children with better expressive language; $\beta = -0.05$).

Predictors: Blood Pressure, Cortisol, and Physical Activity

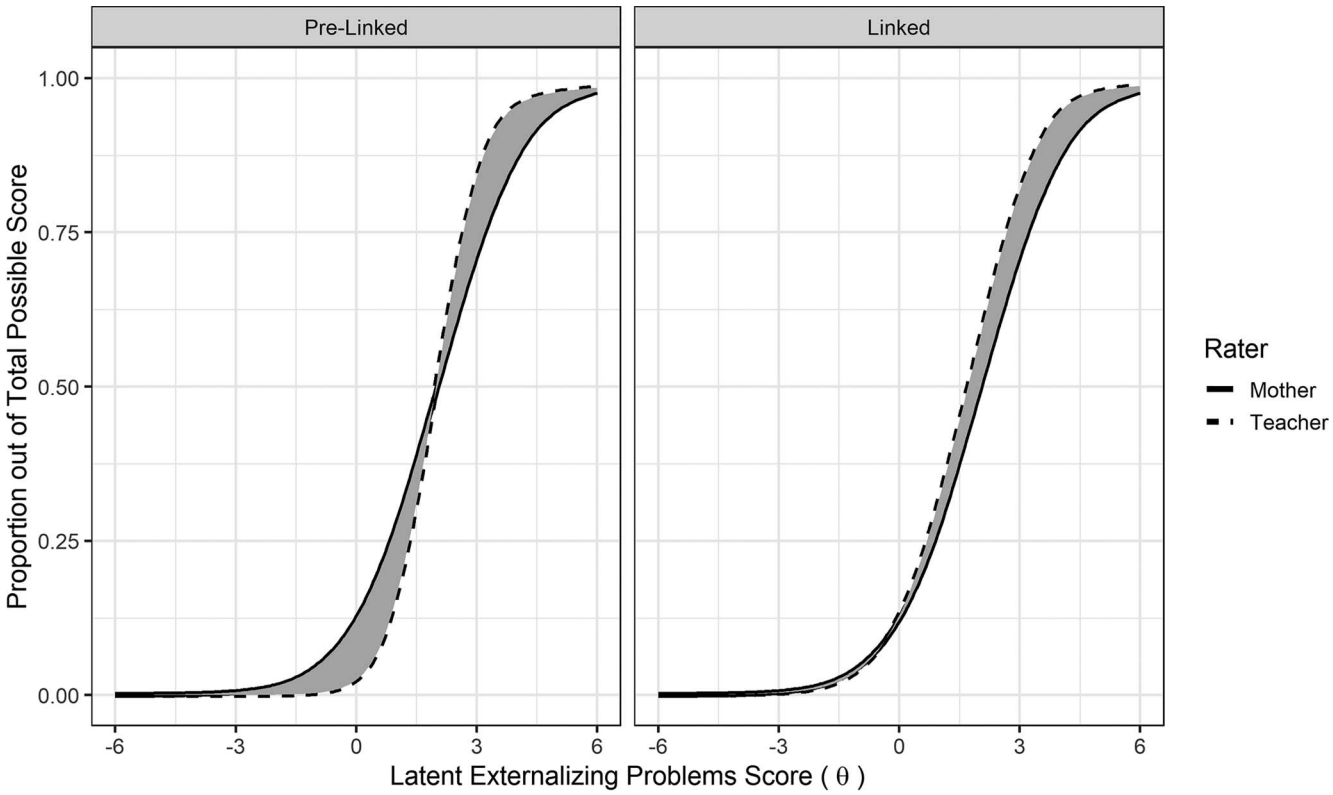
Next, we added age 15 blood pressure, cortisol, and physical activity to the model as predictors of the ending values of externalizing problems at age 15 (see Supplementary Table S13 in the online supplemental material). Neither blood pressure, nor cortisol, nor physical activity were significantly associated with externalizing problems at age 15 ($|\beta s| \leq .04$). The associations between language ability and externalizing problems remained similar.

Discussion

Externalizing problems show changing behavioral manifestations with development (i.e., heterotypic continuity). Externalizing problems often present in overt forms in early childhood (e.g., temper tantrums) whereas externalizing problems tend to present in covert or indirect forms in adolescence and adulthood (e.g., substance use; Miller et al., 2009). Moreover, different informants

Figure 4

Test Characteristic Curves of Prelinked Compared to Linked Scores for Mother- and Teacher-Rated Externalizing Problems at Age 6 Using the Common Items



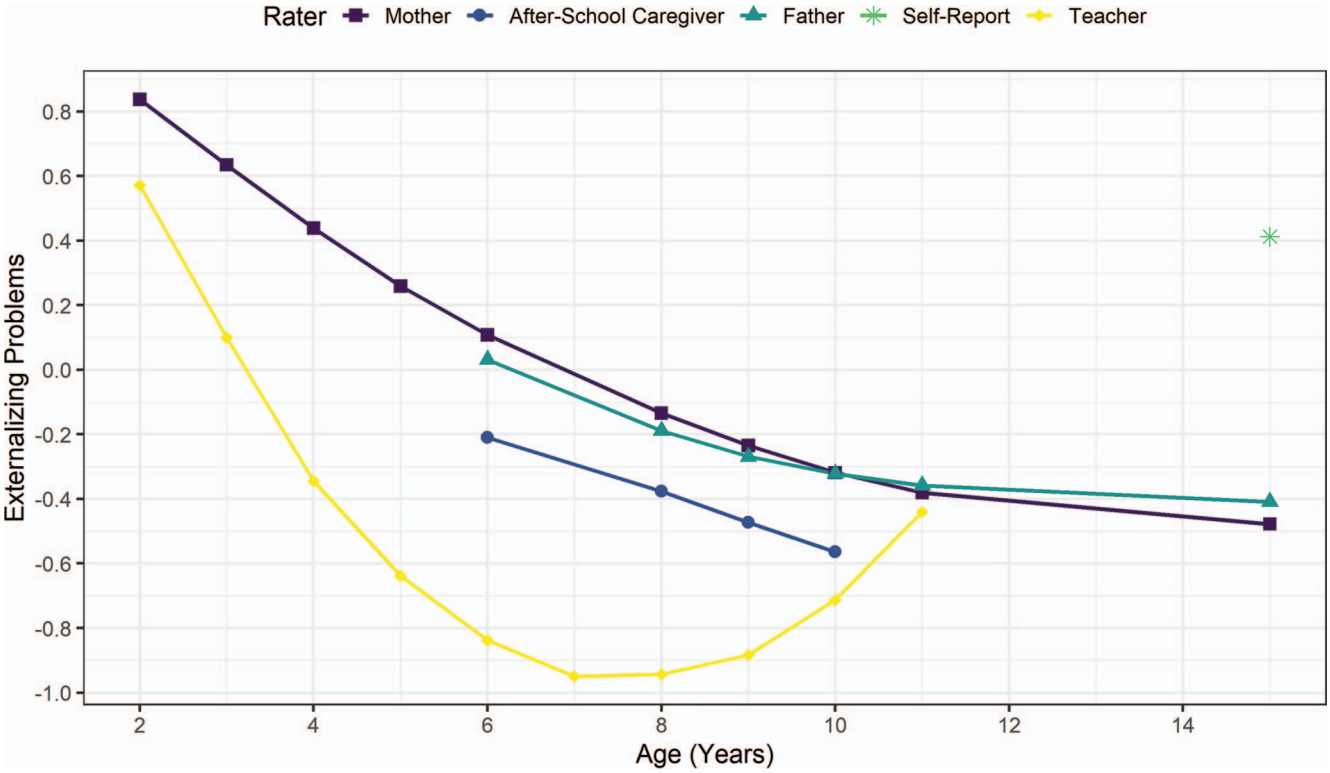
Note. The test characteristic curves of the linked scores were more similar than the test characteristic curves of the prelinked scores, especially in the middle of the distribution (−2 to +2 standard deviations of the mean), where most scores reside.

are useful at different ages when assessing a person's externalizing problems. Although parents and teachers may be important informants of a person's externalizing problems in early childhood (De Los Reyes & Kazdin, 2005), it may also be important to assess peer- and self-report in adolescence (Achenbach et al., 1987). Thus, different informants and measures may be necessary to capture people's change in externalizing problems across time. Many RDoC constructs including inhibitory control (Petersen, Hoyniak, et al., 2016) and negative valence systems (Weems, 2008) also demonstrate heterotypic continuity and may require different measures across ages to maintain development relevance. In addition, scores from the same psychophysiological measure may change in meaning with age (Fox et al., 2007). The challenge of using different informants and measures of a construct across time is ensuring that the same construct is assessed in a comparable way across development. To address this, we created a developmental scale using an IRT approach to vertical scaling and put each informant's and measure's scores on the same developmental scale. In vertical scaling, measures that assess the same construct but differ in severity or discrimination are placed on the same scale. The IRT approach to vertical scaling links two measures scales' by equating the severity and discrimination of their common items. To our knowledge, this is the first study to demonstrate how to combine different informants and measures of a construct across development in ways that still allow assessing absolute change (i.e., changes in a person's level of externalizing problems across time, and changes in means and variances across time).

Creating a developmental scale of externalizing problems across six informants, five measures, and 13 years led to several important advances to better integrate a developmental perspective with RDoC. First, it allowed us to chart trajectories of externalizing problems across a lengthy developmental span from early childhood to adolescence (ages 2–15). Second, it allowed considering multiple informants simultaneously to gain a more comprehensive understanding of a child's externalizing problems. Third, it allowed ratings from different informants to show different trajectories. We observed that teachers, afterschool caregivers, and other caregivers rated children as showing lower levels of externalizing problems compared to ratings by parents. This could reflect systematic differences in children's behavior across the home and school contexts, or it could reflect that teachers see a wider range of children compared to parents and have a better sense of what is developmentally typical. Moreover, fathers rated children as having higher levels of externalizing problems compared to mothers' ratings at age 15. Furthermore, caregivers'/teachers' ratings showed curvilinear growth curves (decreases from early to middle childhood and increases into adolescence) that were not observed in ratings by parents. The decrease in externalizing problems from

Figure 5

Model-Implied Trajectories for Children's Externalizing Problems by Rater



Note. Externalizing problems (latent factor scores) were linked to be on the same developmental scale by using the item response theory approach to vertical scaling. See the online article for the color version of this figure.

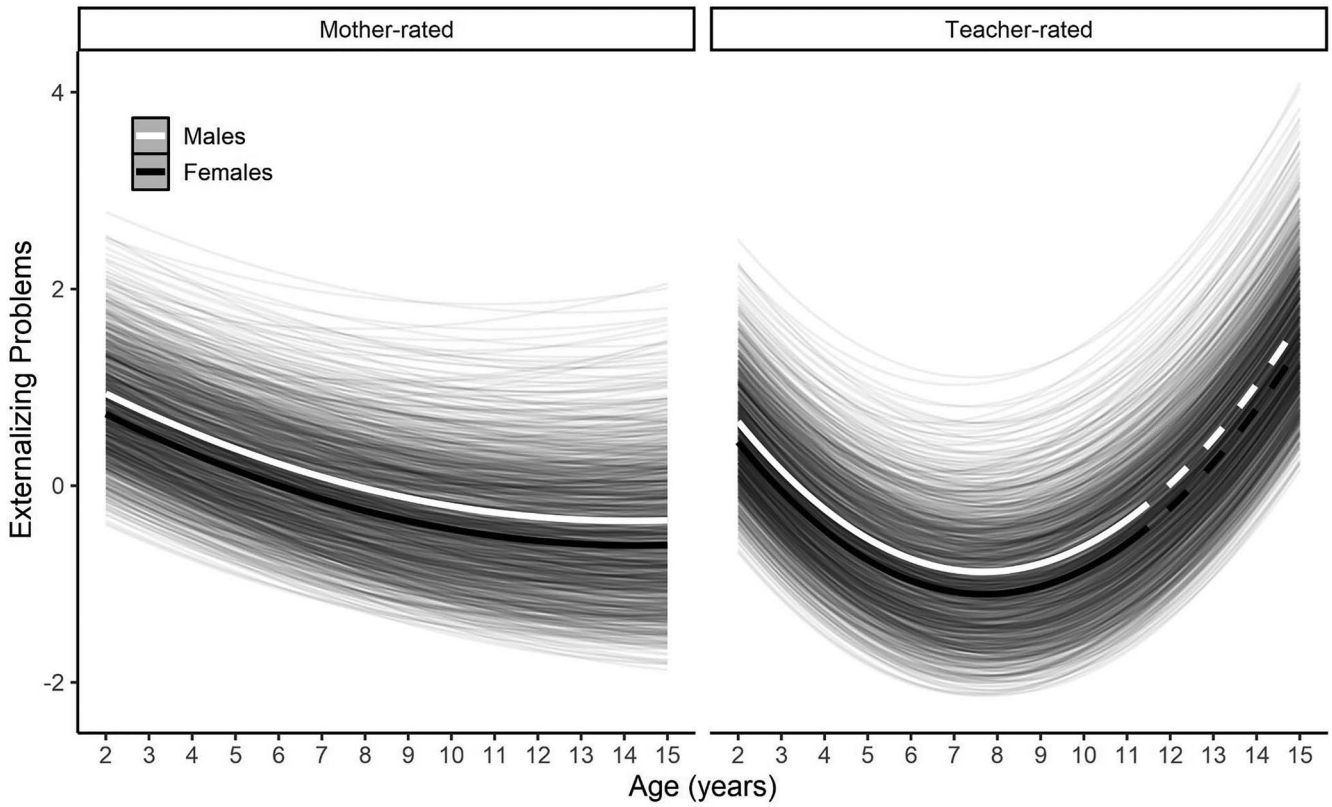
early to middle childhood and increase from middle childhood to adolescence is consistent with prior findings (Petersen, Bates, Dodge, et al., 2015). We also observed that self-report of externalizing problems showed the highest levels of all informants. Overall, the rater role explained 10% of the variance in externalizing problems, over and above the linear and quadratic trajectories. These rater differences may be important to account for in future research. Nevertheless, it also suggests that ratings of externalizing problems are not consistently considerably higher for a particular rater role (mothers vs. fathers vs. teachers, etc.), and that much of the apparent rater discrepancies (.20 ≥ interrater correlations ≤ .56) could reflect context-specific behavior or reporter-specific bias.

Fourth, creating a developmental scale of externalizing problems allowed examining early risk and protective factors across levels of analysis as predictors of change in externalizing problems over time and in their ultimate levels of externalizing problems in adolescence. We also controlled for biobehavioral processes in adolescence, consistent with RDoC aims. We observed that poorer verbal comprehension at age 3 was associated with higher initial levels externalizing problems, and that the association was enduring such that children with poorer verbal comprehension continued to show more externalizing problems when they were 15 years old. Although poorer expressive language skills at age 3 were associated with higher initial levels of externalizing problems, having poorer expressive language did not show enduring effects; children with poorer expressive language skills tended to show greater decreases in externalizing problems over time and showed no statistically significant differences in externalizing problems at age 15 (compared to children with better expressive language). The association between verbal comprehension and externalizing problems held controlling for blood pressure, cortisol, and physical activity. This suggests that differences in blood pressure, cortisol, and physical activity at age 15 may not be mechanisms that explain the association between early verbal comprehension and later externalizing problems.

These findings contribute to a robust literature demonstrating that language ability predicts the development of behavior problems (for a review and meta-analysis, see Chow et al., 2018), and externalizing behavior problems in particular (Petersen et al., 2013; Petersen & LeBeau, in press). Our findings that verbal comprehension had a more enduring association (than expressive language) with the development of later externalizing problems are also consistent with the meta-analytic findings by Chow and colleagues (2018) that receptive language showed stronger associations with later behavior problems compared to expressive language. The association of receptive language with the enduring development of externalizing problems could reflect the importance of language as a tool for private speech and self-regulation (Petersen et al., 2015), or it could reflect that poorer language skills might lead to difficulty labeling one's emotions and emotion

Figure 6

Individuals' Model-Implied Trajectories of Mother- and Teacher-Rated Externalizing Problems



Note. Predictions for teachers' ratings after age 11 (dashed lines) are out-of-range of the teacher-reported data.

dysregulation (e.g., Roben et al., 2013). However, this finding warrants further study.

The present study highlights the utility of vertical scaling to account for heterotypic continuity that may be important for applying a developmental perspective to RDoC. Our IRT approach to vertical scaling used common items to link different measures. An alternative approach for vertical scaling with RDoC constructs that could be useful for linking different biological measures (or other measures without common items) would be to assess at least a subset of participants with each of the measures at a given timepoint, and to use linking methods such as linear, equipercentile, or Thurstone scaling to put the measures on the same scale (Kolen & Brennan, 2014). Bayesian approaches have also been used to link measures with no common items (Oleson et al., 2016). IRT is most often used with dichotomous (e.g., true/false, correct/incorrect) or polytomous (e.g., Likert) item/trial-level data that are common in questionnaires and performance-based assessments; however, extensions allow IRT with continuous data (Chen et al., 2019). Factor analysis is another promising approach for vertical scaling of measures with continuous data and is thus useful for linking many behavioral tasks (Petersen, Hoyniak, et al., 2016). In sum, vertical scaling methods are available for many types of measures and data.

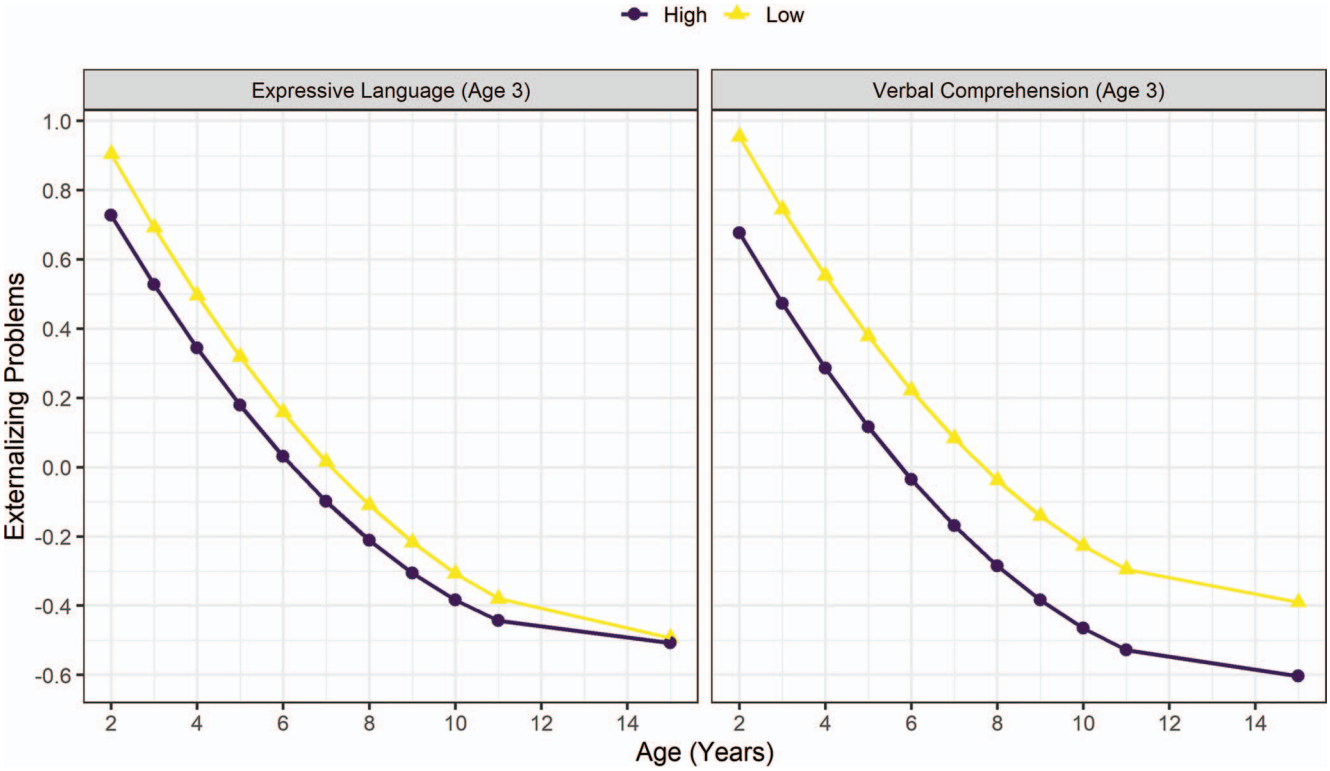
Strengths and Weaknesses

The present study had key strengths. First, we examined multiple informants of children's externalizing problems. Second, we examined a lengthy span of development in a large and diverse sample. Third, we used an IRT approach to vertical scaling to ensure that externalizing problems had construct validity and statistical comparability across the lengthy time frame. IRT and vertical scaling provide better estimates of children's externalizing problem trajectories than an item sum based on classical test theory approaches that assume that all items are equally useful and severe (Lindhiem et al., 2015). Fourth, we examined risk factors across units of analysis, including demographic, socioeconomic, cognitive (language), and biobehavioral levels. Fifth, children's language ability was assessed using an objective, performance-based measure in very early childhood.

The present study also had weaknesses. First, because of the observational design of the study, we cannot make causal inferences. Second, the predictors of externalizing problems were modeled as time-invariant, which limits our ability to understand the developmental processes that link them to externalizing problems. We are unable to rule out the possibility of a reverse direction of effect between language ability and externalizing problems. Nevertheless, studies that have examined language and externalizing

Figure 7

Model-Implied Trajectories of Mother-Rated Externalizing Problems for Children With Low (−1 Standard Deviation of the Mean) Versus High (+1 Standard Deviation of the Mean) Language Ability



Note. Left panel: expressive language; right panel: verbal comprehension. See the online article for the color version of this figure.

problems longitudinally and have examined both potential directions of effect have typically detected stronger associations from language ability to externalizing problems than the reverse (e.g., Petersen et al., 2013; Wang et al., 2018; but see Bornstein et al., 2013). Third, the linking approach we used assumes that item parameters and factor scores are linearly related across measures, raters, and measurement occasions. Nevertheless, evidence suggests that linking was successful across measures, raters, and years (see Figures 2–4).

Conclusion

In the present study, we created a developmental scale of externalizing problems across multiple measures, informants, and timepoints using vertical scaling. Creating a developmental scale allowed us to chart dimensional trajectories of externalizing problems over a lengthy developmental span, and to examine early risk factors across units of analysis that predicted these trajectories. In sum, creating a developmental scale using vertical scaling may be crucial for RDoC's goal to advance a dimensional, multilevel understanding of psychopathology across the life span.

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Supplementary Appendix S1. One-year stability coefficients of externalizing problem ratings within rater.

The mean one-year stability coefficient of externalizing problem ratings within rater was $r = .72$ for mothers' ratings (range: .56 to .80), $r = .76$ for fathers' ratings (range: .75 to .78), $r = .62$ for teachers' ratings (range: .53 to .68), $r = .60$ for afterschool caregivers' ratings (range: .57 to .63), and $r = .37$ for other caregivers' ratings (range: .35 to .39).

Supplementary Appendix S2. Details about the assessment of blood pressure, cortisol, and physical activity.

Blood Pressure

We included a measure of blood pressure as a potential physiological indicator of stress or arousal. Blood pressure has strong input from the sympathetic nervous system, which has shown hypoactivity in externalizing problems (for review, see Hastings et al., 2011). The participant's blood pressure was assessed during a lab visit at age 15 by certified personnel (for more information, see Sabol & Hoyt, 2017). Participants rested at least two minutes prior to getting their blood pressure taken. Blood pressure was taken from the nondominant arm via a blood pressure cuff while participants were seated. Five blood pressure readings were taken at 1-minute intervals. The last three available readings were used to calculate average blood pressure, consistent with prior work (Sabol & Hoyt, 2017). If fewer than three readings were taken, blood pressure was coded as missing. In the present study, blood pressure was operationalized as mean arterial pressure (mm Hg), which is the average blood pressure during a single heartbeat. Mean arterial pressure is an aggregate of systolic and diastolic blood pressure and is time-weighted to account for the fact that systole occupies ~⅓ and diastole occupies ~⅔ of a cardiac cycle. Mean arterial pressure is thus calculated as: $\frac{1}{3} \times \text{systolic blood pressure} + \frac{2}{3} \times \text{diastolic blood pressure}$ (Sesso et al., 2000). Mean arterial pressure is a strong predictor of cardiovascular disease (Sesso et al., 2000), and has been shown to be related to externalizing problems (Hastings et al., 2011).

Cortisol

We included a measure of cortisol as another physiological indicator of stress or arousal. Cortisol levels have been shown to be inversely related to externalizing problems, which may

reflect that externalizing problems are characterized by physiological hypoarousal and fearlessness (Shirtcliff et al., 2005). At age 15, the participant collected their saliva samples at home upon morning awakening for three consecutive school days using a salivette, which were used for later cortisol assay (for more information, see Roisman et al., 2009). Saliva samples were assayed using a highly sensitive enzyme immunoassay (Cat. No.1-0102/1-0112; Salimetrics, http://www.salimetrics.com). The accuracy metrics of the assay are reported in Roisman et al. (2009). Consistent with Roisman et al. (2009), cortisol values (mcg/dL) were averaged across up to three days of data collection. The mean number of days averaged into cortisol values was 2.92 (*SD* = 0.36).

Physical Activity

We included a measure of physical activity as assessed by accelerometer at age 15, given meta-analytics findings that interventions targeting increased physical activity in adolescence result in reductions in externalizing problems (Spruit et al., 2016). Spruit and colleagues hypothesized a number of various mechanisms for reasons why greater physical activity may lead to fewer behavior problems, including physiological effects, learning important social and moral skills through physical activities (e.g., sports), improved self-concept, and greater social inclusion. Participants wore a single-channel accelerometer (Computer Science and Applications, Inc.) for seven consecutive days during a typical school week (for more information, see Nader et al., 2008). Participants were asked to wear the accelerometer on a belt around the waist during waking hours for seven days, including two weekend days and five weekdays, excluding showering, bathing, water sports, or contact sports. On average, participants wore the accelerometer for 6.21 days (*SD* = 0.97), and 841.24 minutes per day (*SD* = 86.99). The accelerometer provided a continuous recording of minute-by-minute movement

counts. We operationalized physical activity as the participant's average percent of time per day spent in moderate to vigorous activity, based on metabolic equivalent tasks (moderate: ≥ 3; vigorous: ≥ 6; Nader et al., 2008).

Supplementary Appendix S3. Tests of uni-dimensionality of externalizing problem items.

One of the assumptions of the item response theory (IRT) models we used is that the externalizing problem items are uni-dimensional—that is, the items have one predominant dimension reflecting the underlying (latent) trait (i.e., externalizing problems). We tested the uni-dimensionality assumption by exploring (a) the ratio of the first to the second eigenvalue and (b) the proportion of variance the first eigenvalue accounts for by age and rater. The first eigenvalue for each age and rater combination ranged from 9.1 to 22.5 and the second eigenvalue ranged from 1.7 to 3.3. One criterion that has been suggested for uni-dimensionality is a ratio of first to second eigenvalues of ≥ 3.0 for an unrotated factor solution (Morizot et al., 2007). The ratio of the first to second eigenvalue ranged from 3.8 up to 12.3, with 30 of the 31 ratio statistics calculated being above 4. The eigenvalues suggested that the first factor accounted for considerably more variance than additional factors, consistent with uni-dimensionality. It has also been suggested that the first factor should account for at least 20% of the variance to meet the assumption of uni-dimensionality (Reckase, 1979). The proportion of variance the first eigenvalue accounted for ranged from .35 to .66, with the majority being between .37 and .5 (20 out of 31).

In sum, the assumption of uni-dimensionality was generally met. Although all of the second eigenvalues were above 1, a rule that is sometimes used for determining how many latent factors underlie the data structure, the ratio of the first to second eigenvalue and proportion of variance accounted for by the first eigenvalue provided evidence that the externalizing problem items were "uni-dimensional" enough for uni-dimensional IRT. We felt that the added complexity of modeling a second latent factor that adds between 5 and 8% of additional variance was not warranted because we were interested in the overall construct of externalizing problems.

Prior research has also suggested that IRT parameter estimates are robust to violations of uni-dimensionality (Harrison, 1986). Given evidence supporting that we approximately met the uni-dimensionality assumption of IRT, we proceeded with the IRT approach to vertical scaling.

Supplementary Appendix S4. Tests of differential item functioning of externalizing problem items.

Method

After fitting IRT models, we examined whether there was differential item functioning (DIF) across ages and raters (comparable to tests of longitudinal measurement/factorial invariance). Lack of DIF across ages and raters for individual items is not an assumption of the linking procedure we used because the linking was performed at the scale-level of the common items (rather than at the item-level). Nevertheless, we examined the extent of DIF to evaluate the degree to which linking across ages and raters was likely to be successful with the common items. DIF examines whether the likelihood of endorsing a particular item differs between groups (in this case, between two ages or raters) for people with the same levels on the construct. To evaluate the extent to which the linking would be successful with the common items, we examined potential item-level and scale-level DIF using the common items between adjacent ages and between raters at ages when we linked raters' scores. We expected some but modest item-level DIF of the common items across ages prior to linking, consistent with a construct that shows theoretically expected changes in its manifestation across development (heterotypic continuity). The Stocking-Lord linking procedure we used to link scores across measures, informants, and years minimizes scale-level latent construct differences rather than item-level differences (that would be minimized by the Haebara procedure). Thus, we expected some items to continue to show DIF even after linking, but we expected that the item-level DIF would be offset by other items on the aggregate. Instead, we expected that the scale-level DIF would show improved performance on the DIF statistics after linking (because the Stocking-Lord linking procedure minimizes scale-level DIF).

To evaluate DIF, we used effect size measures following strategies discussed by Raju (1988) and Meade (2010) that mitigate the multiple testing problems that would occur from testing DIF across hundreds of items (i.e., many items across many ages and multiple raters) in a hypothesis testing framework. The effect size measure computes the difference in the expected scores (i.e. model-implied scores) for an individual item for the focal and reference groups (e.g. age 4 compared to age 5) at specific values of the latent externalizing problems scale. The multiple differences are then averaged across the latent externalizing problems scale (for details, see Meade, 2010). The effect size is interpreted as the average difference in the expected scores on the item across the two groups. There are two versions of this computation, a signed and unsigned difference. The unsigned difference takes the absolute value of the difference in expected scores whereas the signed difference does not. The primary benefit of computing the two statistics is to detect uniform versus non-uniform DIF. Uniform DIF occurs when one group systematically has higher or lower expected scores compared to the other group. Non-uniform DIF occurs when the expected scores change in sign; for example, one group has higher expected scores at lower latent construct scores but has lower expected scores at higher latent construct scores. If unsigned differences are present and signed differences are similar in magnitude to the unsigned differences, uniform DIF is present. If unsigned differences are present and signed differences are smaller than unsigned differences, non-uniform is present. Uniform DIF reflects differences in difficulty (i.e., severity) between groups, whereas non-uniform DIF reflects differences in discrimination (and possibly severity) between groups.

We used a similar approach to examine common item scale-level differences, consistent with the approach we used to examine item-level differences. However, when examining common item scale-level differences, the expected scores would be the expected scores at the

latent construct-level (of the common items) instead of at the item-level. The expected scores at the latent construct-level are equivalent to a sum of the item-level expected scores for the common items. We standardized the expected scores (for the purposes of testing DIF) to remove the effect of a different number of common items used for linking at adjacent ages. For example, we used 26 common items to link mothers' ratings between ages 2 and 3, but we used only 9 common items to link mothers' ratings between ages 3 and 4 (see Supplementary Table S2).

There is not strong guidance for interpreting effect sizes of DIF. We selected effect size cutoffs that would help us identify potentially important DIF while not focusing on negligible differences. At both the item-level and scale-level, we selected effect size cutoffs a priori so that minor DIF would represent a 5% difference in expected scores, whereas moderate DIF would represent a 10% difference in expected scores. To achieve this, for determining the effect size of item-level DIF, we used effect sizes thresholds of 0.1 and 0.2 for evidence of minor and moderate DIF, respectively. For instance, an effect size of 0.1 would indicate that the expected scores for one group are on average 0.1 score points different from the expected scores of the other group. The expected score range is from 0 to 2, so an effect size of 0.1 would indicate a 5% difference in expected scores (i.e., 0.1 / 2 = 5%). For scale-level DIF, we used effect size thresholds of 0.05 and 0.1 for minor and moderate DIF, respectively. We used more stringent effect size thresholds for scale-level DIF because we standardized the expected scores to range from 0 to 1 instead of ranging from 0 to the total number of score points (i.e., the total number of score points on the scale would reflect the number of items times two, with two reflecting the total number of score points on a single item). The effect size cutoffs were half the size for scale-level DIF compared to the effect size cutoffs for the individual items due to the standardization, ranging from 0 to 1 for the scale level, compared to ranging from 0 to 2 for the individual items.

Thus, effect size cutoffs for both item-level and scale-level DIF were comparable such that minor DIF would represent a 5% difference in expected scores, whereas moderate DIF would represent a 10% difference in expected scores.

Results

DIF Between Ages

Item-level DIF. Out of the 711 common items from creating the developmental scales within a rater, 1 item showed evidence of DIF in terms of discrimination and 111 items showed evidence of DIF in terms of severity. The percentage of items showing DIF (i.e., had effect size measures greater than 0.1) between ages ranged from 8% to 23% across raters, although the majority of these items showed only minor levels of DIF. Rates of moderate DIF ranged from 0% to 8% across raters. Teachers' ratings showing the highest rates of moderate DIF after linking, with about 8% of the 261 common items showing evidence of moderate DIF. Fathers' ratings showed the most evidence of minor DIF with about 16% of the 141 common items showing evidence of minor DIF and there was no evidence of any items continuously showing DIF across all ages. There were only two items that showed DIF across three pairs of ages: one item within the father developmental scale and another item in the teacher developmental scale. For these items, there was no evidence of systematic item-level DIF in the same direction. The severity shift was positive or negative with no apparent pattern. Supplementary Figure S1 shows the distribution of unsigned effect size statistics by rater both before and after linking. The figure illustrates that the majority of the items showed no evidence of DIF across ages. For the items that showed evidence of DIF across ages, we also examined non-uniform DIF. We flagged items that showed unsigned effect sizes greater than 0.1 and also had signed effect size statistics less than 0.05 in absolute value. Before linking, one item for mother, father, and teacher showed

evidence of non-uniform DIF across ages. After linking, only the father-rated item remained as showing evidence of non-uniform DIF across ages.

Scale-level DIF. We also evaluated DIF at the scale-level to determine the extent to which the developmental scales were placed on the same scale within a rater. Of all four raters where a developmental scale was created and a total of 26 linkages examined, there was only one adjacent age linking that showed evidence of scale-level DIF after linking. This instance of DIF occurred for the teachers' ratings between ages 4 and 5, which reflected a change from the other caregivers' ratings on the Caregiver–Teacher Report Form (C–TRF) at age 4 to the teachers' ratings on the Teacher's Report Form (TRF) at age 5. This instance of DIF is classified as a DIF between ages within-rater because other caregivers and teachers were classified as the same rater role for purposes of linking (see Method section of the manuscript for more details).

DIF Between Raters

Item-level DIF. Finally, we also explored potential DIF between raters. The percentage of items that showed some level of DIF between raters ranged from 13% to 83% across rater comparisons prior to linking and this percentage ranged from 10% to 58% across rater comparisons after linking. Even though some items showed some level of DIF, a majority of these were minor DIF with only six out of 108 items evaluated showing moderate DIF: three items differed between mothers' and teachers' ratings, and three items differed between mothers' and self-report. Of the items that showed DIF, only six of 108 items showed non-uniform DIF prior to linking, and no items showed non-uniform DIF after linking. Therefore, although there was evidence of item-level DIF, the linking improved the magnitude of DIF and also removed all non-uniform DIF.

Scale-level DIF. We also examined potential scale-level DIF between raters. There was

evidence of minor DIF for one of the scales prior to linking between mothers' and teachers' ratings at age 6; however, after linking there was no evidence of scale-level DIF and all DIF effect sizes were less than 0.01.

Discussion

In summary, we observed some evidence of DIF but generally observed that linking successfully smoothed out the DIF at the scale-level, which provides support that our procedure for linking scores across ages and raters was successful. We observed some item-level DIF, but relatively few items showed DIF for a given rater at a given age. Moreover, where item-level DIF was observed, the effect sizes tended to be small, suggesting negligible DIF. The greatest number of instances of DIF at the item- and scale-level occurred when linking other caregivers' ratings on the C–TRF at age 4 to teachers' ratings on the TRF at age 5. In particular, items rated by other caregivers showed lower severity than items rated by teachers, which suggests that other caregivers endorsed higher rates of externalizing problems compared to teachers. The differences in severity between ratings by other caregivers' and teachers is not particularly surprising because it coincided with multiple simultaneous changes: (1) the age of the child (age 4 versus age 5) and the likely decreases with externalizing problems from ages 4 to 5, (2) the rater role (other caregiver versus teacher), (3) the likely context in which the child's behavior was observed (e.g., home/daycare/preschool versus school), and (4) the measure (C–TRF versus TRF). Thus, we exercise caution in interpreting the linking between other caregivers' ratings on the C–TRF at age 4 and teachers' ratings on the TRF at age 5. However, no other instances of DIF were observed across raters. In general, linking appeared to be successful across both ages and raters, especially for mothers' ratings from ages 2–15, fathers' ratings from ages 6–15, teachers' ratings from ages 5–11, other caregivers' ratings from ages 2–4, and self-report at age

15.

Differences in severity are expected across a lengthy developmental span and are unlikely to be serious threats to measuring the same construct. Compared to differences in severity, differences in discrimination are potentially more serious because they may reflect that an item does not reflect the same construct for some raters at some ages. However, changes in discrimination may instead reflect meaningful developmental shifts in the construct (heterotypic continuity) even though the items still reflect the theoretical content of the construct, as was likely the case in the present study given the strong empirical basis and content validity of the measure we used. Nevertheless, most of the DIF we observed reflected differences in severity (uniform DIF) rather than differences in discrimination (non-uniform DIF). We observed very little evidence of non-uniform DIF at the item-level (only one item after linking), and no instances of non-uniform DIF at the scale-level, further supporting that we were measuring the same construct at all ages.

Despite considerable research on DIF and measurement invariance, there is not clear guidance in the literature on how to proceed in the case of DIF (or failed measurement invariance) because there is no test to determine whether the difference reflects a change in the manifestation of the construct (i.e., heterotypic continuity), changes in the functioning of the measures, or some combination of the two (Knight & Zerr, 2010). Nevertheless, we examined the effect size of DIF and it was modest. Our vertical scaling approach accounted for DIF by estimating a separate IRT model at each age and for each rater, thus allowing items' parameters to change over time and to differ across raters, and using scaling parameters to link the scores across ages and raters to "smooth out" the DIF at the construct-level. In sum, there are theoretical and empirical considerations when determining whether we measured the same construct in an

equivalent way over time, and the totality of the evidence suggests that we did.

Supplementary Appendix S5. Details of vertical scaling (linking scores across informants, measures, and ages).

We fit a separate IRT model for each rater at each age, resulting in 31 IRT models (see Table 1 for the 31 rater-by-age instances). For example, we fit a separate IRT model for mothers' ratings at age 5 and mothers' ratings at age 6. Each IRT model estimates latent factor scores that represented a child's level of externalizing problems. We then linked externalizing problem scores across informants, measures, and ages to be on the same scale. See Figure 1 for a visualization of the measure to which each other measure was linked.

We used IRT to link the scores across informants, measures, and ages based on their common items. When linking any pair of measures in the present study, some items were shared across measures (i.e., common items) and some items were not shared (i.e., unique items). The IRT approach to linking minimizes differences between the probability of a person endorsing the common items across the two given measures to be linked. That is, we linked measures' scales so their common items had similar severity and discrimination at the scale-level by minimizing the differences in their test characteristic curves of the common items (i.e., lessening the gap between the two curves; see Figures 2–4). We describe examples below.

As an example, we linked mothers' ratings at age 3 on the Child Behavior Checklist (CBCL) 2–3 to mothers' ratings at age 4 on the CBCL 4–18 using the common items of the CBCL 2–3 and CBCL 4–18. Common items across the CBCL 2–3 and CBCL 4–18 included items such as "destroys own things." When we linked scores across years or informants from the same measure, all items were common items[1]. For example, we linked mothers' ratings at age 5

[1] However, any items that had a different number of response options endorsed across ages or rater roles were dropped from the linking. For example, if all mothers used only response options 0 or 1 for a given item at age 5, but the mothers used the 0, 1, and 2 response options for the same item at age 6, this item was not used in the linking.

on the CBCL 4–18 to mothers' ratings at age 6 on the CBCL 4–18 using all of their items (all of their items were common items because the items came from the same measure). The number of common items for each pair of measures to be linked is in Supplementary Table S2.

Our IRT approach to vertical scaling applied three steps to link scores from different measures to be on the same scale. First, we fit separate IRT models for each rater at each age (described above). Second, we estimated the test characteristic curve for the common items of each of the pair of measures to be linked. The test characteristic curve represents the probability of endorsing the items (i.e., the proportion out of the total possible score) as a function of a child's latent level of externalizing problems. Third, we estimated scaling parameters to make the test characteristic curves of the common items of each measure more similar. We estimated scaling parameters as the linear transformation (i.e., intercept and slope parameter) that, when applied to the second measure (see Equations 3–4), minimizes differences between the probability of a person endorsing the common items across the two measures. The scaling parameters that we used to link each pair of measures are in Supplementary Table S7. We describe an example below.

See Figure 4 for an example of test characteristic curves of the common items of mother- and teacher-rated externalizing problems at age 6. The left panel of the figure illustrates the test characteristic curves for the common items before the linking process (i.e., the model-implied proportion out of total possible scores on the common items as a function of the latent externalizing problems score for mothers' and teachers' ratings at age 6). The right panel of the figure illustrates the test characteristic curves for the common items after the linking process. The gap between the mother- and teacher-rated test characteristic curves (depicted by gray shading) indicates different probabilities of endorsing the common items across the measures

(i.e., different severity and/or discrimination of the common items), where larger differences reflect scores that are less comparable. Discrimination is depicted by the steepness of the slope at the inflection point of the test characteristic curve. Severity is represented by the value on the x-axis at the inflection point of the test characteristic curve. Linking uses linear scaling parameters to minimizes differences between the discrimination and severity of the common items. We estimated scaling parameters to minimize the differences in the mothers' and teachers' test characteristic curves at age 6. The scaling parameters to link teachers' ratings on the TRF at age 6 to mothers' ratings on the CBCL 4–18 at age 6 were: *A* (slope linking constant) = 1.74, and *B* (intercept linking constant) = -1.44 (see Supplementary Table S7). The left panel of the figure indicates that, prior to linking, mothers' ratings showed somewhat lower discrimination than teachers' ratings at age 6. The right panel shows considerably smaller differences between the two test characteristic curves, which provides empirical evidence that the linking successfully placed the latent externalizing problem scores across raters on a more comparable scale (i.e., more similar discrimination and severity of the common items). In general, we observed successful linking across ages and raters (see Figures 2–4).

We linked all measures directly or indirectly to the scale of mothers' ratings at age 6. For example, we linked mothers' ratings at age 5 directly to mothers' ratings at age 6 because they were at adjacent ages. By contrast, we linked mothers' ratings at age 4 indirectly to mothers' ratings at age 6 via mothers' ratings at age 5, using a process of linking and chaining. To do this, we first linked mothers' ratings at age 4 to the scale of mother' ratings at age 5, and then linked the mothers' ratings at age 4 on the age 5 scale to the age 6 scale. As an example of linking across raters, teachers' ratings at age 5 were indirectly linked to mothers' ratings at age 6 via teacher's ratings at age 6 (see Figure 1). We first linked scores within-rater (see Equation 5), and

then linked scores across raters to link scores to mothers' ratings (see Equation 6). After linking factor scores from all raters and at all ages to be on the scale of mothers' ratings at age 6, we used the linked factor scores as the child's estimated level of externalizing problems for a given rater and age in subsequent growth curve models.

Supplementary Appendix S6. Growth curve model formulas.

$$Y_{ij} = \beta_0 + b_{00i} + \epsilon_{ij}$$
$$Y_{ij} = \beta_0 + \beta_1(\text{age}_{ij} - 15) + \beta_2(\text{age}_{ij} - 15)^2 + b_{00i} + b_{10i}(\text{age}_{ij} - 15) + \epsilon_{ij}$$
$$Y_{ij} = \beta_0 + \beta_1(\text{age}_{ij} - 15) + \beta_2(\text{age}_{ij} - 15)^2 + \beta_3\text{rater}_{ij} + b_{00i} + b_{10i}(\text{age}_{ij} - 15) + \epsilon_{ij}$$
$$Y_{ij} = \beta_0 + \beta_1(\text{age}_{ij} - 15) + \beta_2(\text{age}_{ij} - 15)^2 + \beta_3\text{rater}_{ij} + b_{00i} + b_{10i}(\text{age}_{ij} - 15) + b_{20i}(\text{age}_{ij} - 15)^2 + \epsilon_{ij}$$
$$Y_{ij} = \beta_0 + \beta_1(\text{age}_{ij} - 15) + \beta_2(\text{age}_{ij} - 15)^2 + \beta_3\text{rater}_{ij} + \beta_4(\text{age}_{ij} - 15) \times \text{rater}_{ij} + b_{00i} + b_{10i}(\text{age}_{ij} - 15) + \epsilon_{ij}$$
$$Y_{ij} = \beta_0 + \beta_1(\text{age}_{ij} - 15) + \beta_2(\text{age}_{ij} - 15)^2 + \beta_3\text{rater}_{ij} + \beta_4(\text{age}_{ij} - 15) \times \text{rater}_{ij} + \beta_k\text{Demographics}_{ik} + b_{00i} + b_{10i}(\text{age}_{ij} - 15) + \epsilon_{ij}$$
$$Y_{ij} = \beta_0 + \beta_1(\text{age}_{ij} - 15) + \beta_2(\text{age}_{ij} - 15)^2 + \beta_3\text{rater}_{ij} + \beta_4(\text{age}_{ij} - 15) \times \text{rater}_{ij} + \beta_k\text{Demographics}_{ik} + \beta_5 EL_i + \beta_6 EL_i \times (\text{age}_{ij} - 15) + b_{00i} + b_{10i}(\text{age}_{ij} - 15) + \epsilon_{ij}$$
$$Y_{ij} = \beta_0 + \beta_1(\text{age}_{ij} - 15) + \beta_2(\text{age}_{ij} - 15)^2 + \beta_3\text{rater}_{ij} + \beta_4(\text{age}_{ij} - 15) \times \text{rater}_{ij} + \beta_k\text{Demographics}_{ik} + \beta_5 VC_i + \beta_6 VC_i \times (\text{age}_{ij} - 15) + b_{00i} + b_{10i}(\text{age}_{ij} - 15) + \epsilon_{ij}$$
$$Y_{ij} = \beta_0 + \beta_1(\text{age}_{ij} - 15) + \beta_2(\text{age}_{ij} - 15)^2 + \beta_3\text{rater}_{ij} + \beta_4(\text{age}_{ij} - 15) \times \text{rater}_{ij} + \beta_k\text{Demographics}_{ik} + \beta_5 EL_i + \beta_6 EL_i \times (\text{age}_{ij} - 15) + \beta_k\text{Biological}_{ik} + b_{00i} + b_{10i}(\text{age}_{ij} - 15) + \epsilon_{ij}$$
$$Y_{ij} = \beta_0 + \beta_1(\text{age}_{ij} - 15) + \beta_2(\text{age}_{ij} - 15)^2 + \beta_3\text{rater}_{ij} + \beta_4(\text{age}_{ij} - 15) \times \text{rater}_{ij} + \beta_k\text{Demographics}_{ik} + \beta_5 VC_i + \beta_6 VC_i \times (\text{age}_{ij} - 15) + \beta_k\text{Biological}_{ik} + b_{00i} + b_{10i}(\text{age}_{ij} - 15) + \epsilon_{ij}$$

Note: Y_{ij} is the externalizing problems factor score for person *i* at time *j*. $\beta_0, \ldots \beta_k$ are fixed-effect terms representing the unstandardized estimate of the association between the predictor and externalizing problems. b_{0i}, b_{1i}, and b_{2i} are random effects representing person-specific deviations from the intercept, linear slope, and quadratic slope respectively. ϵ_{ij} are within-person error terms for person *i* at time *j*. Demographics_{ik} represents a set of *k* demographic covariates used to account for potential differences as a function of sex, ethnicity, and income-to-needs ratio. Biological_{ik} represents a set of *k* bio-behavioral covariates used to examine

differences as a function of cortisol, blood pressure, and physical activity. The focal predictors of interest were β_5 and β_6 representing the association of expressive language and verbal comprehension with intercepts and slopes, respectively, of externalizing problems.

The data structure for a single rater would represent repeated measures nested within the participant. Because we included ratings from multiple informants of a given child, there are possibly multiple ratings for a given participant at a single time point. As such, the effect of rater role is considered cross classified rather than nested. That is, each rater does not provide a rating for each participant at every time point; rather, each rater provided a rating for a given participant at some time points based on the SECCYD data collection design. This more complicated cross-classified data structure was modeled by treating the data as repeated measures nested within the participant, by treating the effect of rater role as a fixed (rather than random) effect.

Treating rater role as a fixed effect has a few potential issues with the mixed models used. First, it is has been consistently shown that misspecifying the random effect structure does not lead to bias in the estimates of the fixed parameters which are of most interest in this study (Kwok et al., 2007; LeBeau, 2016; Murphy & Pituch, 2009). Thus, prior evidence provides support for the modeling approach we used in the current study. By contrast, misspecifying the random effect structure could lead to standard errors that are biased (Kwok et al., 2007; LeBeau, 2016; Murphy & Pituch, 2009). However, we corrected for the potential random effect misspecification by adding the rater role as fixed parameters, which should remove the variance associated with raters from the random effects, thus providing a correction factor for the standard errors. Treating raters as fixed parameters also impacts the types of inferences that can be made and who the inferences can be generalized to. With the rater role as a fixed effect, we made the assumption that these rater roles, i.e., mothers, fathers, teachers, afterschool caregivers, other caregivers, and self-report, would be the

most likely to provide ratings for externalizing problems in practice. The extent to which other rater roles are assessed, these study results may not generalize to those raters. We were also interested in exploring the extent to which the rater roles yielded different trajectories of participants' externalizing problems, which was more directly testable by treating the rater role as fixed instead of random.

Our modeling approach was also supported empirically. For example, the R^2 for the fixed effects was about 10% when modeling only the linear and quadratic trajectories with no other effects added to the model. The rater role fixed effect was added next which increased the R^2 for the fixed effects to 20% (an additional 10% of variance explained). The percent of variance explained by rater role was as large as the percent of variance explained by the trajectory terms. Furthermore, this explained variance by the rater role fixed effects resulted in a reduction in the residual variance component associated with the level 1 or repeated measurements in the model, from 0.727 to 0.595. Finally, as a sensitivity check, we fit the cross-classified model and the results were very similar in terms of R^2 explained, except instead of the explained variance being attributed to the fixed effects, it was included as part of the random component. For example, the cross-classified model that estimated a random effect for each rater role and included the linear and quadratic trajectory terms had nearly identical R^2 for random effects of 53% compared to the R^2 of 52% for the model that treated rater role as a fixed effect. These results suggest that we successfully adjusted for the effect of rater role with our approach, and suggest that not modeling this term would have resulted in the potential for significant bias in the standard errors and inferences made from the mixed model.

Supplementary Appendix S7. Tests of systematic missingness and how missing data were handled.

Tests of Systematic Missingness

We observed some systematic missingness of externalizing problem scores as a function of demographic and socioeconomic factors. The number of time points that a child had ratings of externalizing problems differed as a function of the child's sex and ethnicity, and the family's income-to-needs ratio. Girls had more time points of ratings on average compared to boys (t[1,360.70] = -2.05, p = .040). Whites had more time points of ratings on average compared to African Americans (t[214.89] = 3.28, p = .001) but not compared to Hispanics (t[92.03] = 0.63, p = .532). The children's number of time points of ratings was positively associated with the families' income-to-needs ratio (r[1,271] = .12, p < .001). Therefore, we included the child's sex, the child's ethnicity, and the family's income-to-needs ratio as covariates in the final models.

How We Handled Missing Data

We modeled externalizing problem trajectories using a linear mixed model (LMM). Longitudinal LMM analyzes data in long format, where each participant has multiple rows: i.e., one row for each informant-by-timepoint combination. Therefore, the analyses use all available data on each child across the measurement occasions (when they have scores on the predictors). For example, if a child drops out of the study after the first two measurement occasions, LMM still uses the child's data for the first two measurement occasions. LMMs assume that the data are missing at random or completely at random. As a sensitivity test, we also examined findings after multiple imputation to account for missing data across ages and raters (as described below). Findings with multiple imputation were substantially similar, so we present results from the raw data.

Multiple Imputation

As a sensitivity test, we also examined findings after multiple imputation to account for missing data across ages and raters. To account for missingness across ages and raters, we expanded the data matrix to have rows for all possible raters at the ages those raters were intended to be assessed (i.e., mothers: ages 2, 3, 4, 5, 6, 8, 9, 10, 11, 15; fathers: ages 6, 8, 9, 10, 11, 15; teachers: ages 5, 6, 7, 8, 9, 10, 11; after-school caregivers: ages 6, 8, 9, 10; other caregivers: ages 2, 3, 4; self-report: age 15). We did not impute scores for raters at ages those raters were not intended to be assessed (e.g., self-report at age 2) because those columns would have had no observed data, which would have resulted in an overly sparse matrix for imputation.

We multiply imputed 100 data sets with the model variables using the mice package (van Buuren & Groothuis-Oudshoorn, 2011) in R. To account for longitudinal data in imputation, we used the 2l.pan function for imputing missing data at level 1 (i.e., time-varying externalizing problems), according to a mixed model, as described by van Buuren (2018). We included a quadratic term for age in the imputation model to allow externalizing problems to show non-linear change over time. We allowed the linear and quadratic terms for age to have random effects in the imputation of externalizing problems, to allow children to have different slopes. We included the time-invariant predictors as fixed effects. We used the 2lonly.pmm function to impute missing data at level 2 (i.e., time-invariant variables), which uses predictive mean matching (van Buuren, 2018). This multilevel imputation approach has proven successful with longitudinal data (Huque et al., 2018; Lüdtke et al., 2017; Vink et al., 2015).

Supplementary Appendix S8. Nested growth curve model comparisons.

We conducted several nested growth curve model comparisons to identify the best fitting form of change. First, we fit an unconditional means model (allowing each child to have different means) and an unconditional growth model (allowing each child to have different intercepts and slopes). Results from the unconditional means model are in Supplementary Table S8. Results from the unconditional growth model are in Supplementary Table S9. The unconditional growth model (AICc = 67,481.61) fit significantly better than the unconditional means model (AIC = 71,447.35; $\chi^2[4] = 3{,}973.70$, $p < .001$), indicating that children differed in their slopes.

We fit four models to develop the initial baseline trajectory prior to adding other predictors. Given the considerable trajectory differences as a function of rater role (a model that adjusted for rater role fit significantly better than the unconditional growth model; $\chi^2[3] = 2{,}623.90$, $p < .001$), we adjusted for rater role in each model. First, we fit a linear model trajectory with random intercepts and slopes (AICc = 64,863.68). Second, we fit a linear model that allowed for different linear trajectories for each rater role (AICc = 64,704.38), which fit significantly better than the previous model ($\chi^2[3] = 165.30$, $p < .001$). Third, we added a fixed quadratic term to the model (AICc = 63,758.19), which fit significantly better than the previous model ($\chi^2[1] = 948.20$, $p < .001$). Finally, we allowed the quadratic trajectories to vary based on rater role (AICc = 62,894.04), which fit significantly better than the previous model ($\chi^2[3] = 870.16$, $p < .001$). We also considered a model that included a random quadratic effect, but this model was not able to converge due to insufficient variance in the quadratic term. The model with random linear and fixed quadratic slopes that varied by rater role showed the best fit and had the smallest AICc, so it was used as the baseline model with which subsequent models were

compared. Results from the baseline growth model that accounts for the effects of rater role are in Supplementary Table S10.

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Supplementary Table S1. Correlation matrix of model variables.

Variable	Age	Sex	Income-to-Needs Ratio	African American	Hispanic	Externalizing Problems	Mean Arterial Pressure	Cortisol	Physical Activity	Vocabulary	Expressive Language
Age	–										
Sex	n/a	–									
Income-to-Needs Ratio	n/a	.01	–								
African American	n/a	.00	-.22***	–							
Hispanic	n/a	.00	-.06*	-.07*	–						
Externalizing Problems	-.20***	-.12***	-.11***	.10***	.01	–					
Mean Arterial Pressure	n/a	-.23***	-.05	.05	-.03	.05***	–				
Cortisol	n/a	.14***	.11***	-.08*	.02	-.06***	-.06	–			
Physical Activity	n/a	-.33***	-.03	.11*	.03	.06***	.01	-.05	–		
Vocabulary	n/a	.20***	.31***	-.35***	-.12***	-.18***	-.08*	.04	-.08†	–	
Expressive Language	n/a	.16***	.17***	-.19***	-.09***	-.11***	-.11***	.03	-.08†	.57***	–
% Missingness	0.00	0.00	6.67	0.00	0.00	39.79	37.24	36.36	55.87	15.10	17.16
M	7.55	0.48	2.86	0.13	0.06	-0.20	83.77	0.36	5.66	97.85	96.88
SD	3.49	0.50	2.61	0.34	0.24	1.11	5.89	0.18	3.50	15.85	14.53

Note: *** $p < .001$; * $p < .05$; † $p < .10$; all *p*s two-tailed. "n/a" indicates that the association of the variable with age is not applicable because the variable is treated as time-invariant.

Supplementary Table S2. The number of common items for each pair of measures.

Measure	CBCL 2–3	CBCL 4–18	C–TRF	TRF	YSR
CBCL 2–3	26				
CBCL 4–18	9	33			
C–TRF	18	14	40		
TRF	10	27	16	34	
YSR	8	30	14	27	30

Note. "CBCL" = Child Behavior Checklist, "C–TRF" = Caregiver–Teacher Report Form, "TRF" = Teacher's Report Form, "YSR" = Youth Self-Report. Numbers on the diagonal represent the total number of items in the Externalizing scale for that measure (e.g., the CBCL 4–18 has 33 items). Numbers below the diagonal represent, for that pair of measures, the number of items that are common to both of the measures. The number of unique items can be calculated by subtracting the number of common items from the total number of items. For instance, the CBCL 4–18 has 6 unique items when compared with the TRF (i.e., 33 total items minus 27 common items). Conversely, the TRF has 7 unique items when compared with the CBCL 4–18 (i.e., 34 total items minus 27 common items).

Supplementary Table S3. Cronbach's alpha estimates of internal consistency of externalizing problem scores by age and rater.

	Age (Years)										
	2	3	4	5	6	7	8	9	10	11	15
Mother	.88	.89	.88	.89	.89	–	.89	.89	.89	.89	.91
Father	–	–	–	–	.88	–	.88	.90	.91	.91	.91
Teacher	–	–	–	.94	.93	.94	.95	.95	.95	.95	–
After-School Caregiver	–	–	–	–	.92	–	.92	.92	.91	–	–
Other Caregiver	.91	.92	.95	–	–	–	–	–	–	–	–
Self-Report	–	–	–	–	–	–	–	–	–	–	.86

Note: "–" indicates not applicable because the particular rater did not provide ratings at the given time point.

Supplementary Table S4. Descriptive statistics of externalizing problems by age and rater.

	Age (Years)										
M	2	3	4	5	6	7	8	9	10	11	15
Mother	0.77	0.66	0.69	0.11	0.00	–	-0.13	-0.24	-0.30	-0.34	-0.49
Father	–	–	–	–	0.03	–	-0.18	-0.24	-0.38	-0.33	-0.41
Teacher	–	–	–	-0.91	-0.85	-0.86	-0.78	-0.84	-0.76	-0.50	–
After-School Caregiver	–	–	–	–	-0.21	–	-0.40	-0.44	-0.58	–	–
Other Caregiver	0.55	0.41	-0.47	–	–	–	–	–	–	–	–
Self-Report	–	–	–	–	–	–	–	–	–	–	0.41

	Age (Years)										
SD	2	3	4	5	6	7	8	9	10	11	15
Mother	0.79	0.80	0.80	0.91	0.93	–	0.94	0.94	0.98	0.96	0.98
Father	–	–	–	–	0.89	–	0.89	0.95	0.98	0.97	0.96
Teacher	–	–	–	1.05	1.07	1.08	1.16	1.09	1.11	1.17	–
After-School Caregiver	–	–	–	–	1.04	–	1.07	1.03	1.07	–	–
Other Caregiver	0.98	1.05	1.13	–	–	–	–	–	–	–	–
Self-Report	–	–	–	–	–	–	–	–	–	–	0.87

Note: "–" indicates not applicable because the particular rater did not provide ratings at the given time point.

Supplementary Table S5. Percentage of participants with externalizing problem scores at different numbers of time points.

	# of Time Points											
Rater	0	1	2	3	4	5	6	7	8	9	10	11
Mother	8.1	2.2	4.8	1.7	2.2	3.9	2.2	3.8	4.2	11.4	55.6	–
Father	26.0	9.0	5.9	7.0	8.8	13.6	29.8	–	–	–	–	–
Teacher	17.2	1.8	3.0	3.7	5.6	8.6	20.2	40.1	–	–	–	–
After-School Caregiver	67.2	15.2	8.1	6.2	3.4	–	–	–	–	–	–	–
Other Caregiver	27.3	25.1	20.7	26.9	–	–	–	–	–	–	–	–
Self-Report	29.8	70.2	–	–	–	–	–	–	–	–	–	–
Total	7.6	2.1	4.8	1.7	1.7	2.8	1.8	2.5	2.0	4.4	13.1	55.6

Note: "–" indicates not applicable because the particular rater did not provide ratings at the given number of time points. Percentages in a row may not sum exactly to 100.0% because of rounding error.

Supplementary Table S6. Correlation matrix of externalizing problem scores by rater.

Rater	Mother	Father	Teacher	After-School Caregiver	Other Caregiver	Self-Report
Mother	–					
Father	.56***	–				
Teacher	.32***	.32***	–			
After-School Caregiver	.39***	.41***	.44***	–		
Other Caregiver	.20***	n/a	n/a	n/a	–	
Self-Report	.32***	.33***	n/a	n/a	n/a	–

Note: *** $p < .001$; all *p*s two-tailed. "n/a" indicates not applicable because the two raters did not provide ratings at the same time point(s).

Supplementary Table S7. Linking constants for linking scores from different raters and at different ages.

Rater linked from	Rater linked to	Age linked from	Age linked to	*A*	*B*
After-School Caregiver	–	8	6	1.136	-0.252
After-School Caregiver	–	9	8	0.984	-0.460
After-School Caregiver	–	10	9	1.129	-0.199
Father	–	8	6	1.029	-0.263
Father	–	9	8	1.123	-0.096
Father	–	10	9	1.114	-0.201
Father	–	11	10	0.963	0.059
Father	–	15	11	1.062	-0.121
Mother	–	2	3	0.985	0.158
Mother	–	3	4	1.010	-0.056
Mother	–	4	5	0.830	0.667
Mother	–	5	6	0.938	0.136
Mother	–	8	6	1.038	-0.159
Mother	–	9	8	1.037	-0.133
Mother	–	10	9	1.084	-0.970
Mother	–	11	10	0.999	-0.050
Mother	–	15	11	1.116	-0.220
Teacher (Other Caregiver)	–	2	3	0.906	0.145
Teacher (Other Caregiver)	–	3	4	0.750	0.782
Teacher (Other Caregiver)	– (Teacher)	4	5	0.806	0.507
Teacher	–	5	6	1.050	-0.106
Teacher	–	7	6	1.022	-0.026
Teacher	–	8	7	1.029	0.076
Teacher	–	9	8	0.994	-0.078
Teacher	–	10	9	0.970	0.088
Teacher	–	11	10	1.098	0.093
Father	Mother	6	–	0.935	0.041
After-School Caregiver	Mother	6	–	1.254	-0.318
Teacher	Mother	6	–	1.741	-1.439
Self-Report	Mother	15	–	0.856	0.489

Note: "–" indicates that scores were linked to the same rater role or age. "A" = slope linking constant. "B" = intercept linking constant.

Supplementary Table S8. Unconditional Means Model

	B	*SE*	*df*	*p*
Intercept	-0.14	0.02	1199.42	**< .001**
R^2 (fixed effects)	.000			
R^2 (fixed and random effects)	.300			

Note: *p*-values less than .05 in bold.

Supplementary Table S9. Unconditional Growth Model.

	B	β	*SE*	*df*	*p*
Intercept	-0.03	-0.17	0.03	1488.00	**.257**
Time (Linear)	0.19	0.68	0.01	15970.00	**< .001**
Time (Quadratic)	0.02	0.95	0.00	24440.00	**< .001**
R^2 (fixed effects)	.103				
R^2 (fixed and random effects)	.411				

Note: *p*-values less than .05 in bold. “Time” (in years) was centered to set the intercepts at the last time point (age 15). For example, time is coded such that age 2 = -13 and age 15 = 0.

Supplementary Table S10. Baseline Growth Model: Accounting for Effects of Rater Role.

	B	β	*SE*	*df*	*p*
Intercept	-0.46	-0.08	0.03	3044.00	**< .001**
Time (Linear)	0.01	0.88	0.01	23190.00	**.039**
Time (Quadratic)	0.01	1.08	0.00	23710.00	**< .001**
Father	0.14	0.01	0.04	23790.00	**< .001**
Teacher	2.04	-0.16	0.08	23630.00	**< .001**
After-School Caregiver	-0.74	-0.08	0.75	23270.00	.327
Self-Report	0.89	0.17	0.03	23220.00	**< .001**
Time (Linear) × Father	0.02	0.02	0.01	23490.00	.278
Time (Linear) × Teacher	0.68	1.17	0.02	23740.00	**< .001**
Time (Linear) × After-School Caregiver	-0.19	-0.12	0.22	23260.00	.393
Time (Quadratic) × Father	0.00	0.00	0.00	23370.00	.864
Time (Quadratic) × Teacher	0.04	0.92	0.00	23870.00	**< .001**
Time (Quadratic) × After-School Caregiver	-0.02	-0.15	0.02	23250.00	.291
R^2 (fixed effects)	.199				
R^2 (fixed and random effects)	.519				

Note: *p*-values less than .05 in bold. “Time” (in years) was centered to set the intercepts at the last time point (age 15). For example, time is coded such that age 2 = -13 and age 15 = 0. Mothers served as the reference rater to which fathers, teachers, after-school caregivers, and self-report were compared. Interaction terms with time reflect predictions of the linear or quadratic slopes. For instance, “Time (Linear) × Father” reflects differences in slopes of fathers’ ratings (compared to slopes of mothers’ ratings). Self-report was not allowed to predict the slopes because it was assessed at only one time point.

Supplementary Table S11. Growth Model with Demographic and Socioeconomic Factors.

	B	β	*SE*	*df*	*p*
Intercept	-0.28	-0.10	0.05	1478.00	**< .001**
Time (Linear)	0.02	0.88	0.01	11880.00	**.039**
Time (Quadratic)	0.01	1.09	0.00	22340.00	**< .001**
Father	0.15	0.01	0.04	22380.00	**< .001**
Teacher	2.03	-0.17	0.09	22270.00	**< .001**
After-School Caregiver	-0.52	-0.08	0.78	21950.00	.506
Self-Report	0.90	0.17	0.04	21880.00	**< .001**
Time (Linear) × Father	0.02	0.02	0.01	22130.00	.227
Time (Linear) × Teacher	0.68	1.18	0.02	22380.00	**< .001**
Time (Linear) × After-School Caregiver	-0.13	-0.08	0.23	21930.00	.571
Time (Quadratic) × Father	0.00	0.00	0.00	22020.00	.973
Time (Quadratic) × Teacher	0.04	0.93	0.00	22500.00	**< .001**
Time (Quadratic) × After-School Caregiver	-0.01	-0.12	0.02	21930.00	.424
Sex	-0.24	-0.11	0.05	1012.00	**< .001**
African American	0.30	0.08	0.08	1052.00	**.000**
Hispanic	0.16	0.02	0.11	1025.00	.139
Income-to-Needs Ratio	-0.04	-0.09	0.01	1031.00	**< .001**
Time (Linear) × Sex	0.00	-0.01	0.00	970.00	.413
Time (Linear) × African American	0.00	0.00	0.01	1068.00	.509
Time (Linear) × Hispanic	0.01	0.01	0.01	1005.00	.144
Time (Linear) × Income-to-Needs Ratio	0.00	-0.01	0.00	993.50	.215
R^2 (fixed effects)	.233				
R^2 (fixed and random effects)	.517				

Note: *p*-values less than .05 in bold. “Time” (in years) was centered to set the intercepts at the last time point (age 15). For example, time is coded such that age 2 = -13 and age 15 = 0. Mothers served as the reference rater to which fathers, teachers, after-school caregivers, and self-report were compared. Interaction terms with time reflect predictions of the linear or quadratic slopes. For instance, “Time (Linear) × Father” reflects differences in slopes of fathers’ ratings (compared to slopes of mothers’ ratings). Self-report was not allowed to predict the slopes because it was assessed at only one time point. Sex was coded such that male = 0 and female = 1.

In terms of ethnicity, Whites served as the reference group to which Blacks and Hispanics were compared.

Supplementary Table S12. Growth Model with Language Ability.

	Verbal Comprehension as Predictor					Expressive Language as Predictor				
	B	β	*SE*	*df*	*p*	*B*	β	*SE*	*df*	*p*
Intercept	0.37	-0.11	0.18	990.70	**.043**	-0.24	-0.12	0.19	977.80	.199
Time (Linear)	0.00	0.89	0.02	1476.00	.919	-0.03	0.88	0.02	1423.00	.116
Time (Quadratic)	0.01	1.09	0.00	21310.00	**< .001**	0.01	1.09	0.00	20820.00	**< .001**
Father	0.13	0.00	0.04	21400.00	**.001**	0.13	0.00	0.04	20900.00	**.001**
Teacher	2.03	-0.17	0.09	21290.00	**< .001**	2.05	-0.17	0.09	20790.00	**< .001**
After-School Caregiver	-0.56	-0.08	0.80	21010.00	.481	-0.89	-0.09	0.81	20520.00	.270
Self-Report	0.88	0.17	0.04	20940.00	**< .001**	0.89	0.17	0.04	20460.00	**< .001**
Time (Linear) × Father	0.02	0.02	0.01	21170.00	.306	0.02	0.02	0.02	20670.00	.241
Time (Linear) × Teacher	0.68	1.18	0.02	21380.00	**< .001**	0.69	1.19	0.02	20870.00	**< .001**
Time (Linear) × After-School Caregiver	-0.14	-0.09	0.23	20990.00	.537	-0.23	-0.15	0.23	20510.00	.323
Time (Quadratic) × Father	0.00	0.00	0.00	21070.00	.884	0.00	0.00	0.00	20590.00	.989
Time (Quadratic) × Teacher	0.04	0.94	0.00	21490.00	**< .001**	0.04	0.94	0.00	20980.00	**< .001**
Time (Quadratic) × After-School Caregiver	-0.01	-0.13	0.02	20990.00	.393	-0.02	-0.18	0.02	20500.00	.233
Sex	-0.19	-0.08	0.05	955.00	**< .001**	-0.22	-0.10	0.05	938.50	**< .001**
African American	0.22	0.04	0.09	985.00	**.016**	0.34	0.08	0.09	969.00	**< .001**
Hispanic	0.13	0.00	0.11	975.50	.238	0.19	0.02	0.11	956.10	.083
Income-to-Needs Ratio	-0.04	-0.07	0.01	972.90	**< .001**	-0.05	-0.09	0.01	955.80	**< .001**
Time (Linear) × Sex	0.00	0.00	0.00	924.40	.545	0.00	-0.01	0.00	900.40	.403
Time (Linear) × African American	0.01	0.01	0.01	984.40	.148	0.01	0.01	0.01	965.40	.087
Time (Linear) × Hispanic	0.02	0.01	0.01	956.90	.083	0.02	0.01	0.01	931.10	.057
Time (Linear) × Income-to-Needs Ratio	0.00	-0.01	0.00	938.60	.113	0.00	-0.01	0.00	917.10	.056
Verbal Comprehension	-0.01	-0.13	0.00	955.70	**< .001**	–	–	–	–	–
Expressive Language	–	–	–	–	–	0.00	-0.05	0.00	947.30	.790
Time (Linear) × Verbal Comprehension	0.00	0.01	0.00	927.90	.275	–	–	–	–	–
Time (Linear) × Expressive Language	–	–	–	–	–	0.00	0.02	0.00	912.00	**.003**

R^2 (fixed effects)	.249	.242
R^2 (fixed and random effects)	.520	.522

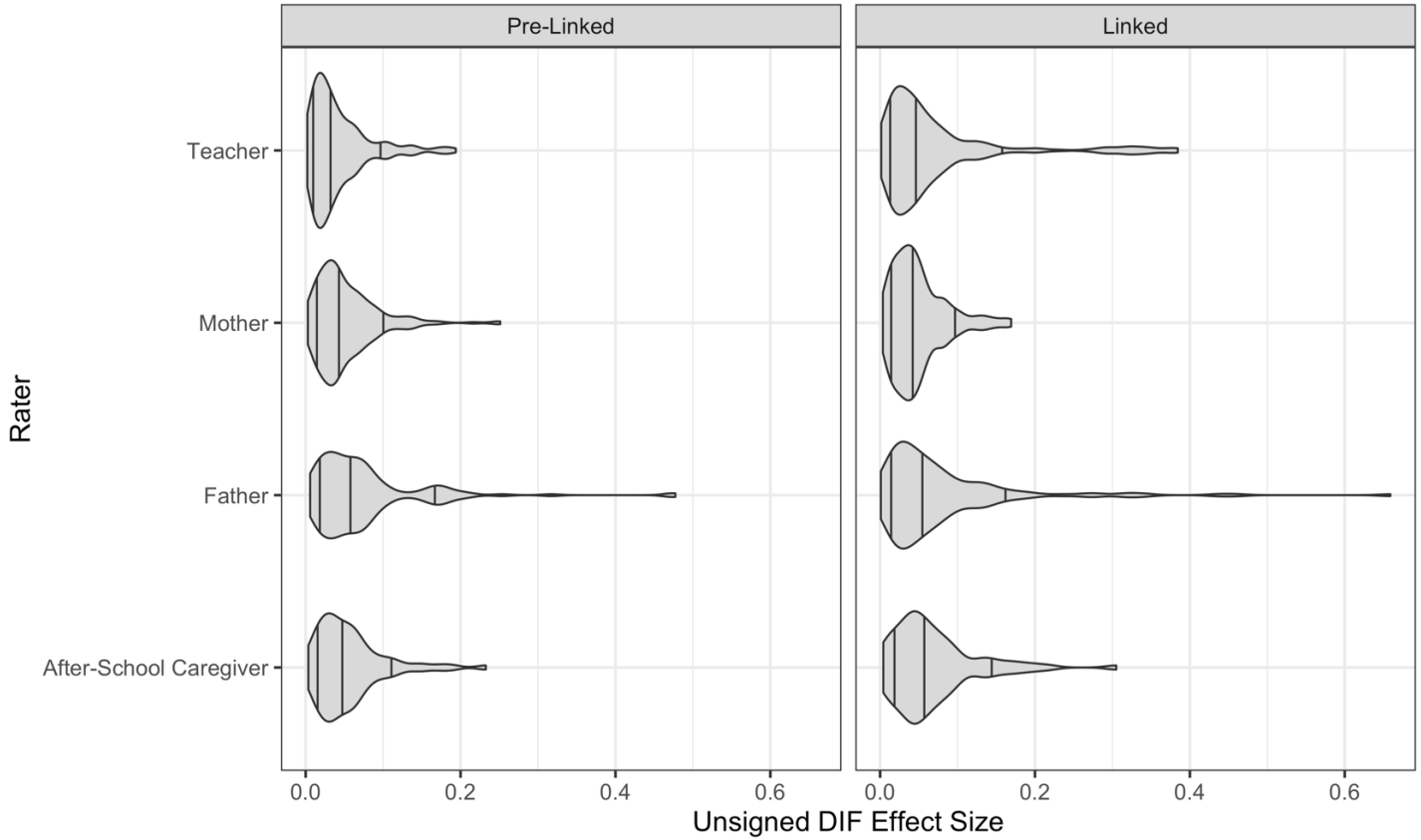
Note: Significant *p*-values in bold. "Time" (in years) was centered to set the intercepts at the last time point (age 15). For example, time is coded such that age 2 = -13 and age 15 = 0. Mothers served as the reference rater to which fathers, teachers, after-school caregivers, and self-report were compared. Interaction terms with time reflect predictions of the linear or quadratic slopes. For instance, "Time (Linear) × Father" reflects differences in slopes of fathers' ratings (compared to slopes of mothers' ratings). Self-report was not allowed to predict the slopes because it was assessed at only one time point. Sex was coded such that male = 0 and female = 1. In terms of ethnicity, Whites served as the reference group to which Blacks and Hispanics were compared. "–" indicates not applicable because the particular term was not estimated in that model.

Supplementary Table S13. Growth Model with Language Ability and Biological Covariates.

	Predicting Verbal Comprehension					Predicting Expressive Language				
	B	β	*SE*	*df*	*p*	*B*	β	*SE*	*df*	*p*
Intercept	0.07	-0.12	0.45	586.30	.871	-0.25	-0.12	0.47	566.30	.598
Time (Linear)	-0.03	0.85	0.02	793.00	.147	-0.06	0.86	0.02	746.30	**.008**
Time (Quadratic)	0.01	1.07	0.00	10610.00	**< .001**	0.01	1.08	0.00	10340.00	**< .001**
Father	0.13	0.01	0.05	10850.00	**.011**	0.13	0.01	0.05	10570.00	**.011**
Teacher	2.09	-0.17	0.12	10770.00	**< .001**	2.12	-0.17	0.12	10490.00	**< .001**
After-School Caregiver	-0.90	-0.10	1.09	10690.00	.410	-0.95	-0.10	1.10	10410.00	.391
Self-Report	0.86	0.16	0.05	10610.00	**< .001**	0.88	0.17	0.05	10330.00	**< .001**
Time (Linear) × Father	0.02	0.03	0.02	10720.00	.291	0.03	0.03	0.02	10440.00	.216
Time (Linear) × Teacher	0.70	1.20	0.03	10810.00	**< .001**	0.70	1.22	0.03	10530.00	**< .001**
Time (Linear) × After-School Caregiver	-0.25	-0.17	0.32	10680.00	.427	-0.26	-0.17	0.32	10400.00	.419
Time (Quadratic) × Father	0.00	0.01	0.00	10670.00	.708	0.00	0.02	0.00	10400.00	.577
Time (Quadratic) × Teacher	0.04	0.95	0.00	10870.00	**< .001**	0.04	0.96	0.00	10590.00	**< .001**
Time (Quadratic) × After-School Caregiver	-0.02	-0.21	0.02	10680.00	.310	-0.02	-0.21	0.02	10400.00	.309
Sex	-0.12	-0.07	0.07	508.70	.092	-0.16	-0.10	0.07	496.00	**.024**
African American	0.20	0.04	0.11	491.50	**.074**	0.32	0.07	0.11	480.10	**.005**
Hispanic	-0.02	-0.03	0.14	469.00	.865	0.02	-0.02	0.15	457.10	.912
Income-to-Needs Ratio	-0.03	-0.06	0.02	473.20	**.041**	-0.04	-0.10	0.02	457.90	**.004**
Time (Linear) × Sex	0.00	0.01	0.01	471.60	.576	0.00	0.01	0.01	458.10	.450
Time (Linear) × African American	0.01	0.01	0.01	499.60	.247	0.01	0.01	0.01	489.10	.241
Time (Linear) × Hispanic	0.01	0.01	0.01	464.20	.262	0.01	0.01	0.01	451.00	.197
Time (Linear) × Income-to-Needs Ratio	0.00	-0.01	0.00	465.00	.388	0.00	-0.01	0.00	447.80	.480
Mean Arterial Blood Pressure	0.00	0.03	0.00	476.30	.256	0.00	0.02	0.00	463.30	.398
Cortisol	-0.25	-0.04	0.14	479.80	.087	-0.24	-0.04	0.15	467.10	.105
Physical Activity	0.01	0.02	0.01	479.40	.413	0.00	0.02	0.01	466.40	.564
Verbal Comprehension	-0.01	-0.17	0.00	474.00	**< .001**	–	–	–	–	–

Expressive Language	–	–	–	–	–	0.00	-0.12	0.00	460.50	.125
Time (Linear) × Verbal Comprehension	0.00	0.02	0.00	478.20	.072	–	–	–	–	–
Time (Linear) × Expressive Language	–	–	–	–	–	0.00	0.03	0.00	458.00	**.002**
R^2 (fixed effects)			.261					.255		
R^2 (fixed and random effects)			.506					.511		

Note: Significant *p*-values in bold. "Time" (in years) was centered to set the intercepts at the last time point (age 15). For example, time is coded such that age 2 = -13 and age 15 = 0. Mothers served as the reference rater to which fathers, teachers, after-school caregivers, and self-report were compared. Interaction terms with time reflect predictions of the linear or quadratic slopes. For instance, "Time (Linear) × Father" reflects differences in slopes of fathers' ratings (compared to slopes of mothers' ratings). Self-report was not allowed to predict the slopes because it was assessed at only one time point. Sex was coded such that male = 0 and female = 1. In terms of ethnicity, Whites served as the reference group to which Blacks and Hispanics were compared. "–" indicates not applicable because the particular term was not estimated in that model.



Supplementary Figure S1. Violin plots of the distribution of unsigned effect size statistics of differential item functioning by rater both before and after linking. Vertical lines correspond to the 10^{th}, 50^{th}, and 90^{th} percentiles.