

Does the Environment Have an Enduring Effect on ADHD? A Longitudinal Study of Monozygotic Twin Differences in Children

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Abstract Environmental factors play a key role in the development of Attention-Deficit/Hyperactivity Disorder (ADHD), but the long-term effects of these factors are still unclear. This study analyses data from 1024 monozygotic (identical) twins in Australia, the United States, and Scandinavia who were assessed for ADHD in Preschool, Kindergarten, Grade 1, and Grade 2. Differences within each twin pair were used as a direct measure of non-shared environmental effects. The Trait-State-Occasion (TSO) model developed by Cole et al. (Psychological Methods, 10, 3–20, [2005](#page-12-0)) was used to separate the non-shared environmental effects into stable factors, and transient factors that excluded measurement error. Stable factors explained, on average, 44 % and 39 % of the environmental variance in hyperactive-impulsive and inattentive symptoms, respectively. Transient effects explained the remaining 56 % and 60 % of variance. The proportion of stable variance was higher than expected based on previous research, suggesting promise for targeted interventions if future research identifies these stable risk factors.

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Attention-Deficit/Hyperactivity Disorder (ADHD) is common among children (Graetz et al. [2001\)](#page-13-0) and causes substantial impairment in school and home life (American Psychiatric Association [APA] [2013\)](#page-12-0). Although it is highly heritable, environmental factors play a key role in determining whether and how ADHD will develop among children with genetic predispositions to the disorder (National Health and Medical Research Council [2009](#page-13-0)). However, it is still unclear if specific environmental factors have a lasting effect on ADHD, or if the environmental variance represents factors with only a transient effect. This study attempts to separate the environmental variance in ADHD into the lasting, transient, and measurement-error components, and estimate the typical duration of the transient effects, using data from monozygotic (MZ; identical) twins and a novel design.

Attention-Deficit/Hyperactivity Disorder (ADHD)

Attention-Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder beginning in childhood and characterised by behavioural symptoms of inattention, hyperactivity, and impulsivity present at age-inappropriate levels (APA [2013\)](#page-12-0). Hyperactivity often becomes apparent earlier than inattentive symptoms and tends to decline over childhood, while symptoms of inattention tend to be more persistent (Lahey et al. [2005](#page-13-0)).

ADHD has been conceptualised as a disorder of executive functioning (Barkley [1997](#page-12-0)). Executive functions develop throughout childhood and adolescence, with inhibition improving rapidly in early childhood, planning improving most during later childhood, and working memory and shifting abilities improving steadily from preschool onwards (Best et al. [2009](#page-12-0)). A study of change in executive functioning abilities during childhood observed substantial improvements in inhibitory control and task-switching abilities between ages 6 to 9 years, but no such increase in children with ADHD (Gupta and Kar [2009](#page-13-0)). Similarly, executive attention abilities which develop through early childhood (Posner et al. [2014\)](#page-13-0) are impaired in children with ADHD (Mullane et al. [2010\)](#page-13-0). These findings suggest that the development of executive functions may be delayed or disrupted in children with ADHD, leaving them behind their peers.

ADHD is highly heritable, with twin studies in children suggesting 70–90 % of the variance between individuals is due to genetic factors, and 10–30 % due to unique environmental factors (specific to each twin; Jepsen and Michel [2006\)](#page-13-0). Most studies found no significant effect of shared environmental factors (those which increase similarity within twin pairs; Jepsen and Michel [2006\)](#page-13-0). When the symptom dimensions are considered separately, heritability is slightly higher for hyperactivity (73 %) than inattention (71 %), and the unique environmental variance shows a sharp increase from childhood to adolescence for hyperactivity, but is relatively stable for inattention (Nikolas and Burt [2010](#page-13-0)). Thus, although each child's genetic makeup (genotype) is largely set from birth, the environmental variance may include influences on ADHD that are potentially malleable, offering an opportunity to alter the trajectory of ADHD.

Several unique environmental factors have been associated with ADHD, including childhood stroke (Max et al. [2002\)](#page-13-0), lead exposure (Nigg et al. [2010\)](#page-13-0), and traumatic brain injury (Yeates et al. [2005](#page-14-0)). Brain injury may cause ADHD symptoms in children who were previously unaffected, and can exacerbate existing ADHD symptoms in others. Streptococcal infection has been implicated as a possible causative factor in some cases of ADHD, believed to be due to damage to the basal ganglia caused by the immune response to the infection (Leslie et al. [2008;](#page-13-0) Peterson et al. [2000\)](#page-13-0). Low birth weight (Breslau et al. [1996;](#page-12-0) Groen-Blokhuis et al. [2011](#page-13-0)) has also been associated with ADHD.

Some psychosocial factors have been identified which may act as unique environmental influences on ADHD symptoms. Though it is now acknowledged that such factors do not cause ADHD independently, they may affect the severity of ADHD symptoms, and contribute to comorbid oppositional symptoms (Barkley [2015](#page-12-0)). Maternal depression, lower household income, and a less-stimulating and supportive home environment have been associated with increased risk of ADHD (Sagiv et al. [2013\)](#page-13-0), and may act as unique environmental influences if they affect children within the same family differently. A more negative parenting approach, with more frequent commands and less frequent praise, has been observed in parents of children with ADHD; however, the direction of this effect is unclear, as this improved when the children took stimulant medication (Danforth et al. [1991](#page-12-0)), and children's ADHD symptoms may interact with parents' own ADHD symptoms to produce poorer parenting behaviour (Wymbs et al. [2015](#page-14-0)).

Research suggests the specific environmental factors contributing to ADHD generally have a short-lived or transient effect. Greven et al. ([2011\)](#page-13-0) analysed inattention and hyperactivity, separately, at ages 7 and 11. At age 11, for both phenotypes, \sim 70 % of the environmental variance (including measurement error) was short-lived and specific to one time point. The balance, \sim 30 %, was shared at ages 7 and 11. However, with just two timepoints, this research sources only some of the detail on the duration of the environmental effects. We would expect some factors, such as brain injury, to have lasting effects on the trajectory of ADHD, while others may have temporary or transient effects. So while previous studies (Greven et al. [2011;](#page-13-0) Price et al. [2005](#page-13-0)) have separated effects which are stable across all timepoints from those unique to each time-point, they offer no way to detect those affecting multiple but not all time-points, nor the duration of these effects.

The Current Study

The current study aims to assess whether environmental influences during early childhood have a lasting effect on the trajectory of ADHD symptoms, or if their effect is transient and if so, how long these transient effects last for.

The MZ Twin Differences Design

Because MZ twins share all of their genes, any differences between them can only be due to the environment (or epigenetic factors), and these environmental effects are defined as unique environment (i.e., those affecting one twin in the pair), as distinct from shared environment effects, which affect both twins in the pair (Plomin et al. [2008\)](#page-13-0). However, as mentioned earlier, most twin studies have found no significant shared environmental effects on ADHD (Jepsen and Michel [2006\)](#page-13-0), so this paper focuses on unique environment effects. These unique environmental effects are quantified by computing difference scores within MZ twin pairs, thereby controlling for any genetic and shared environment effects (Plomin et al. [2008\)](#page-13-0).

Longitudinal Analyses

MZ difference scores allow us to quantify the environmental variance in ADHD, but we need a way to distinguish between lasting and transient effects, and a method to estimate the duration of these effects. Correlations between scores across timepoints indicate the stability over time, but more advanced methods are needed to quantify influences that affect all, some, or only one time-point. For example, if we have calculated MZ difference scores for ADHD at four time-points (Preschool, Kindergarten, Grade 1, and Grade 2), the squared correlations between time-points indicate how much environmental variance at one time-point is shared with another time-point. If time-point 2 and 3 are correlated 0.60, we know 36 % of the environmental influences affecting time-point 2 also affect time-point 3. However, this does not tell us anything about the duration of these effects beyond these two time-points; we cannot distinguish between environmental influences that affect all time-points, multiple but not all time-points, or only one time-point. The 36 % common variance could reflect stable environmental influences affecting all time-points measured in the study; or their effect may diminish over time, affecting multiple, but not all, measurement occasions.

We considered models specifically designed for partitioning variance in longitudinal data. Cholesky Decompositions are frequently used in twin research to segment the variance into portions that are largely stable and transient. We, instead, used the Trait State Occasion (TSO) model (Cole et al. [2005\)](#page-12-0), since it partitions the variance more specifically than the Cholesky. In the TSO model, each observed value (in this case, the MZ difference scores for inattention or hyperactivity) is decomposed into a latent state (or true score) component and a measurement error component. Each state factor can be further decomposed into a latent trait factor comprising stable effects contributing equally to all time-points, and a latent factor representing occasion-specific effects. An autoregressive structure connects the occasion-specific factors, to account for factors which may have short-term stability, such that effects contributing to occasion variance at one time-point also contribute to subsequent time-points, with a decay in magnitude over time (Luhmann et al. [2011](#page-13-0)). With this model, it is also possible to decompose each occasion factor into new variance, and variance carried over from the previous time-point.

It is important to note this study specifically investigates the variance explained by the non-shared environmental effects on ADHD, not the variance in ADHD as a whole. It is also important to note that when describing trait effects as stable in this context, stability refers to relative stability rather than stability of absolute scores (Prenoveau et al. [2011\)](#page-13-0). For example, symptoms of ADHD in children may decline with age (Biederman et al. [2000\)](#page-12-0); however, unless children's scores change relative to their peers, ADHD will be stable over time despite the change in mean scores.

Hypotheses

The children in this study are followed from age 5 to age 8, an age range during which executive and attentional functions are still developing, sometimes making rapid improvements (Best et al. [2009](#page-12-0)). This is also a period during which children's environments may change substantially, with transitions between preschool, kindergarten, and school, and the social and academic demands of these various settings. Thus, these years could be a period of fluctuation of individual differences in ADHD symptoms as well as of the environmental factors contributing to them.

This study predicts the majority of unique environmental variance across ages 5 to 8 will be occasion variance, suggesting environmental influences are largely transient rather than stable. This is suggested by findings from previous research, which suggest stable influences account for around 30 % of the environmental variance in ADHD (Greven et al. [2011\)](#page-13-0), and that unique environmental variance is unstable during early years (age 3 to age 7) relative to later years (age 7 to 12; Rietveld et al. [2004\)](#page-13-0).

Method

Participants

Participants were 1024 monozygotic twins (490 male, 534 female) aged approximately 5 years $(M=4$ years 11 months, $SD = 3$ months) at the first stage of testing. Mean age of participants at each stage are presented in Table 1. Participants were recruited from the Australian Twin Registry, the Colorado Twin Registry in the United States, and the Medical Birth Registries in Norway and Sweden, as part of a longitudinal study on early reading development (Byrne et al. [2002\)](#page-12-0). Data was only gathered from children whose first language was English (in Australia and the US), Norwegian (in Norway), or Swedish (in Sweden). The ethnicity of participants in each country was predominantly white. In the US, 8 % were Hispanic or Latino, 3 % were African American, and 2 % were Asian. Data was gathered from both monozygotic and dizygotic twins, but only data from monozygotic

Table 1 Mean and standard deviation of participant age at each wave of testing, by country

Preschool	Kindergarten	Grade 1	Grade 2	
4.8(0.3)	6.1(0.4)	7.0(0.4)	8.0(0.4)	
4.9(0.2)	6.3(0.3)	7.4(0.3)	8.5(0.3)	
5.1(0.2)	6.7(0.3)	7.7(0.3)	8.7(0.3)	
5.0(0.1)	6.8(0.3)	7.7(0.3)	8.7(0.3)	
4.9(0.2)	6.3(0.4)	7.4(0.4)	8.4(0.4)	

twins was included in the current study. Zygosity was determined by DNA samples in 83 % of children, a method that is close to 100 % accurate (Chen et al. [2010](#page-12-0)), and structured questioning in the remaining children, which is 95 % accurate (Nichols and Bilbro [1966\)](#page-13-0). There was more attrition among participants in Australia (50 %) and Sweden (51 %) than the United States (6 %) and Norway (7 %), but the cohort of participants in the final wave did not differ from the full cohort in gender ratio, mean age, or difference scores (unique environmental variance).

Measures

The Disruptive Behaviour Rating Scale (DBRS; Barkley and Murphy [1998](#page-12-0)) was used to assess symptoms of ADHD. Parents completed the questionnaire for each twin in Preschool, Kindergarten, Grade 1, and Grade 2. The scale includes nine questions assessing hyperactivity-impulsivity and nine assessing inattention, based on the symptoms listed in the DSM-IV-TR (APA [2000](#page-12-0)). Questions were answered on a Likert-type scale of four possible responses: not at all, just a little, pretty much, and very much, which were coded as 0, 1, 2, and 3, respectively. Scores were added to produce a total score for hyperactivity-impulsivity (which, for clarity, will be referred to as "hyperactivity" hereafter) and one for inattention, each ranging from 0 to 27.

The DBRS is valid for assessing ADHD in young children (Friedman-Weieneth et al. [2009](#page-12-0)) and has good internal consistency (Cronbach's alpha 0.94; Friedman-Weieneth et al. [2009\)](#page-12-0). In the current sample, internal consistency was good (Cronbach's alpha 0.91) and 1-year test-retest stability was 0.65 for hyperactivity and 0.61 for inattention (between Kindergarten and Preschool).

Data Preparation

As the TSO model requires two indicators (observed variables) at each time-point (Cole et al. [2005\)](#page-12-0), the sets of questions in the DBRS measuring hyperactivity and inattention were each split in two by alternating items and summed to create two half-scales: Half1 and Half2. The half-scales had good internal consistency (Cronbach's alpha 0.84 for Half1 and 0.81 for Half2), and 1-year test-retest stability ranging from 0.57 to 0.62 for hyperactivity and 0.53 to 0.57 for inattention. Previous research (Cole et al. [2008](#page-12-0); Olatunji and Cole [2009\)](#page-13-0) has used similar approaches to create multiple indicators from a single scale.

For each twin pair, a difference score was calculated for Hyperactivity Half1, Hyperactivity Half2, Inattention Half1, and Inattention Half2 at each of the four time-points, by subtracting the scores for twin 2 from those of twin 1. Histograms of the difference scores were examined to check

for skew, kurtosis, and univariate outliers; the data appeared normally distributed with no problematic outliers.

Missing Values

The Missing Values Analysis procedure in SPSS (IBM Corp. [2012\)](#page-13-0) was used to analyse missing data. The percentage of data missing was 8.3 %, 16.2 %, 22.7 %, and 30.1 % at Preschool, Kindergarten, Grade 1, and Grade 2, respectively. This pattern of attrition is typical of longitudinal data, as participants may move away, drop out of the study, or become unreachable between time-points. The Expectation-Maximization algorithm in SPSS was used to deal with missing data. This method produces similar results to the FIML method built into Amos (IBM [2010](#page-13-0)), which failed in this study. This generated an estimated variance-covariance matrix which was reformatted as outlined in the Amos User Guide (Arbuckle [2011](#page-12-0)) and used for the subsequent SEM analyses.

Data Analysis

Structural Equation Modelling (SEM)

IBM SPSS Amos Version 20 (IBM Corp. [2011](#page-13-0)) was used for Structural Equation Modelling (SEM). Amos uses Maximum Likelihood (ML) estimation to estimate the values of model parameters (Kline [2011](#page-13-0)). ML estimation assumes the variables are unstandardised, missing data are dealt with prior to estimation, and the variables exhibit multivariate normality (Kline [2011\)](#page-13-0). In addition, SEM assumes the sample size is adequate, the variables are continuous and normally distributed, and the model is identified (University of Texas [2012\)](#page-13-0). The current study adhered to these assumptions.

Model Identification To be identified, the model must have degrees of freedom above zero, and a scale must be assigned to each latent variable (Kline [2011](#page-13-0)). The model degrees of freedom is equal to the number of items in the variance-covariance matrix minus the number of parameters to be estimated; in the current study, there are 36 items in the matrix, so up to 35 parameters can be estimated. Unlike observed variables, latent variables do not have a scale of measurement, so must be assigned one. This is typically done by fixing one of the regression weights from each latent variable to 1 (Kline [2011\)](#page-13-0).

The Trait-State-Occasion (TSO) Model

As previously mentioned, the current study uses the Trait State Occasion (TSO) model developed by Cole et al. [\(2005\)](#page-12-0), pictured in Fig. [1.](#page-4-0) This model requires longitudinal data from at least three time-points (waves of measurement). The model requires two measures of the same construct at each timepoint. This makes it possible to distinguish between

Fig. 1 Four-wave Trait-State-Occasion (TSO) model

measurement error, which is specific to each measure, and occasion variance, which is specific to each measurement occasion. The autoregressive parameter (a_1-a_3) in Fig. 1) between two occasion factors indicates how much occasion variance is carried over from one time-point to the next. This allows occasion variance to have some short-term stability.

To understand how the stable trait variance and transient occasion variance are derived from the observed data, it is useful to think of the model in terms of a series of decompositions. First, the variance of each observed variable (Half1 or Half2) is decomposed into a measurement error component and a state factor. The state factor may be conceptualised as the true level of hyperactivity or inattention at each time-point. Each state factor is then decomposed into two components: The stable trait factor and an occasion factor specific to that time-point. The trait factor includes all influences on the construct that are stable over time, whereas the occasion factor includes influences with a transient or short-lived effect. Each occasion factor (except at the first time-point) can be further decomposed into (1) effects carried over from the previous time-point and (2) a *disturbance* component, which reflects sources of variance new to that time-point. The occasion factors follow an autoregressive structure, meaning each occasion factor depends to some extent on the occasion factor of the previous time-point (Cole et al. [2005](#page-12-0)). This allows occasion variance to have some short-term stability, so transient influences can contribute to variance at one or more timepoints with an effect that decays in magnitude over time

(Luhmann et al. [2011](#page-13-0)). This stability parameter ("a" in Fig. 1) thus reflects how much variance is carried over from one time-point to the next.

The Current Study

The current study fit two versions of the Trait State Occasion (TSO) model, one for inattention and one for hyperactivity. The observed variables in each model were the MZ twin difference scores for Half1 and Half2 of inattention or hyperactivity. As the difference scores are a measure of unique environmental variance, the latent state variables represent the total unique environmental variance at each time-point of the study.

After estimating the model in Amos, a series of modifications to the model were tested. A chi-square difference test was performed after each change to determine whether the change significantly improved model fit (Kline [2011\)](#page-13-0). If so, the change was retained.

Results

Descriptive Statistics

Descriptive statistics for the raw scores obtained by participants on the DBRS and the MZ twin difference scores are shown in Table [2.](#page-5-0) Raw scores for hyperactivity declined

Table 2 Means, standard deviations, and ranges of raw DBRS scores and MZ difference scores

		Hyperactivity		Inattention			
Time-point	\boldsymbol{n}	M(SD)	Range	\boldsymbol{n}	M(SD)	Range	
Raw scores							
Preschool	950	7.0(4.6)	$0 - 25$	874	5.6(3.9)	$0 - 22$	
Kindergarten	868	5.2(4.3)	$0 - 23$	856	4.6(3.6)	$0 - 19$	
Grade 1 800		4.6(4.2)	$0 - 24$	798	4.9(4.0)	$0 - 22$	
Grade 2	722	4.0(3.9)	$0 - 23$	720	5.0(4.0)	$0 - 25$	
Difference scores							
Preschool 475		0.3(3.1)	$-11-18$	437	0.1(3.2)	$-14-14$	
Kindergarten 434		0.3(3.0)	$-14-14$	428	0.5(3.2)	$-12-15$	
Grade 1 400		0.1(3.0)	$-14-13$	399	0.1(3.7)	$-15-12$	
Grade 2	361	0.2(3.0)	$-15-15$	360	0.3(3.8)	$-12-14$	

Raw scores are the average of each twin pair

between Preschool and Kindergarten, t (399) = 9.26, p < 0.05, between Kindergarten and Grade 1, t (364) = 2.90, p < 0.05, and between Grade 1 and Grade 2, t (328) = 3.61, p < 0.05. Raw scores for inattention declined between Preschool and Kindergarten, $t(367) = 6.63$, $p < 0.05$. The percentage of phenotypic variance accounted for by environmental factors at Preschool, Kindergarten, Grade 1, and Grade 2, respectively, was 20 %, 22 %, 22 %, and 26 % for hyperactivity and 29 %, 34 %, 35 %, and 37 % for inattention. There were no significant differences in MZ difference scores by gender or country.

Trait-State-Occasion (TSO) Model

Base Models for Hyperactivity and Inattention

Several constraints were placed on the model, as recommend-ed by Cole et al. ([2005](#page-12-0)). The stability parameters (a_1 - a_3 in Fig. [1\)](#page-4-0) between the occasion factors were constrained to be equal, assuming similar stability across each 1-year interval (homogeneity of regression). The disturbances (u_1-u_3) were also constrained to be equal, assuming homogeneity of disturbance variance. Error variances $(e_{11}-e_{42})$ were assumed to be uncorrelated.

The factor loadings and error variances were constrained to be equal across time-points; these constraints constitute an assumption of measurement invariance, meaning the relationship between state factors, half-scales, and errors (the measurement model) is assumed to be the same across all time-points (Donnellan et al. [2012](#page-12-0)). Breaking this assumption may have implications for interpretation of the model (Schmitt and Kuljanin [2008](#page-13-0)), as it may be unclear whether differences between time-points reflect true differences in the construct or differences in the measurement model. However, equal error

variances are typically considered an unnecessarily strict form of measurement invariance (Byrne [2010\)](#page-12-0).

As discussed earlier, a single regression weight for each latent variable must be fixed to 1 for the model to be identified. All factor loadings from the trait factor were also fixed to 1 as, by definition, the trait factor affects all time-points equally (Cole et al. [2005\)](#page-12-0). Finally, as the half-scales are halves of the same questionnaire, it was assumed they would load similarly on the state factor, so their factor loadings $(f_{11}-f_{41})$ and $f_{12} - f_{42}$) were constrained to be equal.

Goodness-of-fit statistics for the base models are shown in Table 3. The chi-square statistic was significant both for hyperactivity, $\chi^2 = 116.82$, $df = 30$, $p < 0.001$, and inattention, χ^2 = 139.79, df = 30, p < 0.001. However, with large sample sizes, small discrepancies cause the chi-square to be significant (MacCallum et al. [1996\)](#page-13-0), and fit indices are preferred (Byrne [2010](#page-12-0)). Scores of 0.95 or above on the CFI, 0.06 or below on the SRMR, and 0.06 or below on the RMSEA suggest the model is a good fit (Hu and Bentler [1999](#page-13-0)). For both models, CFI and RMSEA are outside the recommended ranges. SRMR is outside the recommended range for hyperactivity, but inside the range for inattention.

Alternative Models

Several alternative models, shown in Table [4,](#page-6-0) were tested. In addition, the assumption of measurement invariance was tested by freeing each factor loading to vary across time. This improved the fit of the inattention model (χ^2_{diff} = 15.38, df = 4, p < 0.01, for Half1 and χ^2 - $_{diff}$ = 11.31, df = 4, p < 0.05, for Half2), but not the hyperactivity model, suggesting the measurement invariance assumption was not met for the inattention model. This indicates the relationship between the latent state factor and the half-scales is not completely stable over time, which could reflect changes in how each half-scale loads on the state factor. However, allowing the factor loadings to vary would make the final model underidentified, so they were constrained to be equal for the subsequent analyses.

Table 3 Goodness-of-fit statistics for hyperactivity and inattention base models

χ^2	CFI	RMSEA	SRMR	
116.819*	0.944	0.077	0.062	
139.789*	0.937	0.087	0.040	

CFI Comparative Fit Index, RMSEA Root Mean Square Error of Approximation, SRMR Standardised Root Mean Square Residual $* p < 0.001$

Table 4 Alternative TSO models and results of chi-square difference tests

^a Estimation of the hyperactivity model failed because the covariance matrix between e2, e4, e6, and e8 was not positive definite

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Final Models

Hyperactivity The final model found for hyperactivity (Fig. 2) is similar to the original model outlined by Cole et al. ([2005](#page-12-0)), except the factor loading of Half2 is allowed to vary from the factor loading of Half1, and error terms (e_1-e_8) are allowed to vary across time. This suggests Half1 and Half2 do not load equally on the state factors, contrary to expectation; and that error variance is different across time-points. Fit indices (Table [5](#page-7-0)) suggest the model is a good fit; CFI, RMSEA, and SRMR are all within the recommended ranges (Hu and Bentler [1999\)](#page-13-0). The chi-square value is still significant, χ^2 = 63.42, df = 23, p < 0.001, but, as previously mentioned, this is common when the sample size is large, even in well-fitting models (MacCallum et al. [1996](#page-13-0)).

Variance estimates of all latent factors are significant, $p < 0.001$ (Table [6](#page-7-0)). However, the stability parameter is non-

Fig. 2 Parameter estimates of final Trait-State-Occasion (TSO) model for hyperactivity. Doubleheaded arrows to and from the same variable indicate variance. Variance of u_1 , u_2 , and u_3 are constrained to be equal; variance of e_1 , e_3 , e_5 , and e_7 are constrained to be equal; variance of e_2 , e_4 , e_6 , and e₈ are constrained to be equal; and factor loadings of Half2 were constrained to be equal. Direct effects from Occ_1 to Occ_2 , Occ_2 to Occ₃, and Occ₃ to Occ₄ were constrained to be equal. All paths marked "1" were fixed to 1

Table 5 Goodness-of-fit statistics for hyperactivity and inattention final models

Model	χ^2	CFI	RMSEA	SRMR
Hyperactivity	$63.424**$	0.974	0.060	0.046
Inattention	$26.523*$	0.990	0.058	0.036

CFI Comparative Fit Index, RMSEA Root Mean Square Error of Approximation, SRMR Standardised Root Mean Square Residual ** $p < 0.001$. * $p = 0.003$

significant, $b = 0.09$, $p = 0.16$, indicating negligible occasion factor stability, with less than 1 % of variance carrying over from one occasion factor to the next.

Inattention The final model for inattention (Fig. [3\)](#page-8-0) includes several differences to the base model. Disturbances (u_1-u_3) and error terms (e_1-e_8) vary across time, suggesting different levels of occasion-specific and error variance across timepoints. Adding covariances among the error terms also significantly improved model fit, suggesting shared method effects (effects specific to each half-scale; Cole [2006](#page-12-0)). Although the Chi-square is significant, χ^2 = 26.52, df = 10, p = 0.003, as expected due to the large sample size, all fit indices (CFI, RMSEA, and SRMR) are in the recommended ranges, suggesting good fit.

Variance estimates of all latent variables are significant, $p < 0.001$ (Table 6). The stability parameter is significant, $b = 0.23$, $p < 0.001$, but small, with only 5 % of variance

Table 6 Summary of model parameters estimated in Amos carrying over from one occasion factor to the next. Unlike in the Cole ([2006](#page-12-0)) study, only four of the covariances between error terms are significant to the $p < 0.05$ level. However, all covariances were retained, since removing individual covariances from the model based solely on statistical results, without theoretical rationale for the change to the model, would risk capitalising on chance (Kline [2011\)](#page-13-0).

Variance Decomposition

As explained in the method, each half-scale score is decomposed into measurement error and a latent state factor. In the current study, measurement error accounts for, on average, 32 % of variance in each half-scale for hyperactivity and inattention; the remaining 68 % is explained by state factors (true scores).

Each state factor is then decomposed into stable trait variance and transient occasion variance. From the second timepoint onwards, occasion variance is further decomposed into an autoregressive component and a disturbance factor (variance new to that occasion).

Figure [4](#page-8-0) and Table [7](#page-9-0) show the proportions of variance explained by each component. In support of the hypothesis, transient occasion effects account for over half of the true environmental variance in hyperactivity (56 %) and inattention (61 %). Most of this is variance new to each occasion; less than 1 % (hyperactivity) and around 3 % (inattention) is carried over from the previous occasion. This suggests most

Full table of model parameters is included in [Appendix A.](#page-12-0) Variances of endogenous variables (Occasion2, Occcasion3, Occasion4, State1, State2, State3, and State4) are not estimated in Amos

^a Parameters were constrained to be equal. ^b Mean across all time-points. ^c Parameters were fixed to 1.*** $p < 0.001$

significant covariances, respectively. Direct effects from $Occ₁$ to $Occ₂$, $Occ₂$ to $Occ₃$, and $Occ₃$ to $Occ₄$ were constrained to be equal. All paths marked "1" were fixed to 1

Fig. 4 Percentages of trait and occasion variance at each timepoint for hyperactivity and inattention

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	Hyperactivity									Inattention	
Time-point	State Total	Trait Total	Trait Percentage	Occasion Total	Occasion Percentage (stable, disturbance)	State Total	Trait Total	Trait Percentage	Occasion Total	Occasion Percentage (stable, disturbance)	
Pre-school	2.55	1.06	41 $%$	1.50	59 %	2.23	0.96	43 $%$	1.27	57 $%$	
Kindergarten	2.36	1.06	45 $%$	1.31	55 % (0.5 %, 54.8 %)	2.01	0.96	48 %	1.05	52 % (3.4 %, 48.9 %)	
Grade 1	2.36	1.06	45 $%$	1.31	55 % (0.5 %, 54.8 %)	2.75	0.96	35%	1.80	65 % (2.0 %, 63.2 %)	
Grade 2	2.36	1.06	45 $%$	1.31	55 % (0.5 %, 54.8 %)	2.99	0.96	32%	2.03	68 % (3.2 %, 64.8 %)	
Average			44 %		56 % (0.5 %, 54.8 %)			39 $%$		61 % (2.9 %, 59.0 %)	

Table 7 State, trait, and occasion variance in hyperactivity and inattention at each time-point

Formulae for variance components are in [Appendix B](#page-12-0)

transient environmental influences affect only one time-point of the study, with very few effects spanning two or three timepoints.

Discussion

The current study aimed to assess whether environmental influences during early childhood have a lasting effect on the trajectory of ADHD symptoms, and the duration of these environmental effects. The Trait-State-Occasion (TSO; Cole et al. [2005](#page-12-0)) model was used to partition variance into stable and transient components. As predicted, well over half of the environmental variance in inattention and hyperactivity is transient occasion variance rather than stable trait variance, even after error variance is removed. On average, stable factors explain 44 % of the true environmental variance in the hyperactivity model and 39 % in the inattention model, with the remaining 56 % and 61 % explained by transient factors.

As discussed in the results, the hyperactivity model meets all important assumptions and is a good fit to the data. The two half-scales do not load equally on the state factors, which was unexpected, as they are halves of the same scale (the hyperactivity scale of the DBRS; Barkley and Murphy [1998](#page-12-0)). However, the loadings of Half1 relative to Half2 were similar to the average loadings of the items in a previous factor analysis of the DBRS (Friedman-Weieneth et al. [2009\)](#page-12-0). This is not problematic, and other studies have allowed the loadings to vary (e.g., Hatton et al. [2008](#page-13-0); Schaufeli et al. [2011](#page-13-0)).

The inattention model failed to meet the assumption of measurement invariance, which weakens the interpretations we can make based on this model, as we cannot be certain whether changes over time reflect true changes in the construct (Schmitt and Kuljanin [2008](#page-13-0)). The disturbance factors (u_1-u_3) varied across time-points in the inattention model, which is not problematic, but suggests the amount of new environmental variance differs between time-points. This could reflect changes in children's school settings during this study (preschool, kindergarten, and school).

As discussed in the results, the current study found stable trait factors explain 44 % and 39 % of total true environmental variance in hyperactivity and inattention, respectively (Table 7). The trait factor, by definition, contributes equally to variance at each time-point, representing environmental influences on ADHD that span all 4 years of the study. The remaining variance (56 % for hyperactivity and 61 % for inattention) is explained by occasion factors.

These results appear to contradict previous research, which has found very low stability of unique environmental variance in ADHD. Greven et al. ([2011](#page-13-0)) found that in children aged 11, \sim 30 % of environmental variance in both hyperactivity and inattention had been present at age 7. However, their transient environmental variance included measurement error, unlike the models used herein, which partitioned this error variance separately. In order to compare the results, we can consider the trait and occasion variance as proportions of the total variance in the half-scale scores, rather than proportions of state variance. As mentioned in our results, measurement error accounts for, on average, 32 % of variance in the hyperactivity and inattention half-scales, with the remaining 68 % explained by the state factors. Thus, in our study, trait variance explains 30 % (68 % * 44 %) and 27 % (68 % * 39 %) of the total variance in the half scale scores for hyperactivity and inattention, respectively. These estimates of stable environmental variance are now comparable, and more consistent with, the 30 % observed by Greven et al.

The current study found a marginal difference in stable environmental variance between hyperactivity (44 %) and inattention (39 %), and between the trajectories of these dimensions. In the hyperactivity model, the proportion of stable variance increased marginally from the first time-point to the second time-point, and remained constant from then on (Fig. [4](#page-8-0)). For inattention, the largest change was a decrease between the second and third time-points, tentatively suggesting environmental factors contributing to inattention become less stable between ages 6 and 7. However, as the assumption of measurement invariance did not hold for the inattention model, and due to the small magnitude of the changes, these findings should be interpreted with caution.

Interestingly, the occasion factors show very little shortterm stability. In both models, most occasion variance comes from the disturbance factors (variance new to each timepoint), rather than from the previous occasion. This suggests most of the environmental influences on ADHD have either a very short-lived effect, affecting only one time-point, or a persistent effect on all time-points. Very few effects (less than 1 % for hyperactivity and around 3 % for inattention) span two or three time-points of the study. This raises the question: What is the longer-term trajectory of the trait variance we observed across the preschool to Grade 2 time interval?

Limitations and Future Research

The results of this study should be considered in the context of its limitations. First, although both models were a good fit to the data, the inattention model failed to meet the assumption of measurement invariance, as the factor loadings were inconsistent across time-points. This weakens the interpretations we can make based on this model, as we cannot be sure whether changes over time reflect true changes in the construct or changes in how it is measured (Schmitt and Kuljanin [2008\)](#page-13-0).

Conclusions drawn from this study are also limited by the parent-only reports of ADHD symptoms, and by the 4-year duration. Future research could provide further insight into the long-term effects of environmental factors on ADHD by applying the Trait-State-Occasion model to longer time-frames and different age groups.

Finally, this study did not attempt to identify the specific non-shared environmental factors which have a persistent effect on ADHD. Some environmental factors identified in previous studies, such as childhood stroke (Max et al. [2002](#page-13-0)), lead exposure (Nigg et al. [2010](#page-13-0)), traumatic brain injury (Yeates et al. [2005\)](#page-14-0), low birth weight (Breslau et al. [1996](#page-12-0); Groen-Blokhuis et al. [2011\)](#page-13-0), and psychosocial factors such as a less-stimulating and supportive home environment (Sagiv et al. [2013\)](#page-13-0), could contribute to this non-shared environmental trait variance. Future research could explore this by incorporating such potential risk factors into the TSO model, as predictors of the trait factor (as in Hatton et al. [2008\)](#page-13-0).

Conclusions and Implications

This study used data from monozygotic (identical) twins with a novel design to study the effects of stable trait factors and transient occasion factors on the environmental variance in ADHD, and the duration of these effects. Consistent with past research, the current study found that, once measurement error

was removed, over half of the environmental factors contributing to ADHD were transient, lasting no more than a year (one time-point of the study), with the balance, a non-trivial amount, being stable from preschool through to grade 2.

There appear to be two predominant patterns of environmental influence on ADHD; transient effects contributing to only one measurement occasion, and stable, traitlike effects which persist over the long term. Very little variance was explained by environmental effects between these extremes, spanning 2 or 3 years. This suggests environmental factors contributing to ADHD in the early school years tend to be either enduring or particularly short-lived; there is little evidence here for environmental effects with an intermediate duration of 2 to 3 years. A pertinent question to ask is whether we would expect the stable environmental effects measured here to continue throughout childhood, into adolescence and perhaps adulthood. Research across these age ranges would be required to answer this question; however, if the pattern of environmental variance identified in this study continues without a substantial shift, the stable trait variance would persist.

This trait variance represents environmental factors with potentially long-term effects on the trajectory of ADHD. Although transient effects account for more variance overall, since their effect is so short-lived, identifying the specific factors involved may have little practical benefit. As discussed earlier, this study covers an age range during which children typically transition between school environments with different academic, behavioural, and social demands. The current study tentatively suggests these factors have transient, if any, effects on ADHD. Trait variance could include factors identified earlier such as low birth weight (Breslau et al. [1996\)](#page-12-0), childhood stroke (Max et al. [2003\)](#page-13-0), and traumatic brain injury (Max et al. [2004](#page-13-0)), which could pose difficult targets for intervention efforts; however, exploring further the sources of this variance may uncover factors which are changeable or preventable.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee.

Parameter Estimates for Hyperactivity and Inattention Models.

Table 8 Complete list of model parameters estimated in Amos

Variances of endogenous variables (Occasion2, Occcasion3, Occasion4, State1, State2, State3, and State4) are not estimated in Amos

 a Parameters were constrained to be equal. b Parameter was fixed to 1

 $* p < 0.001$

Appendix B

Variance Decomposition for Hyperactivity

and Inattention Models The variance at each time-point was decomposed into proportions accounted for by trait, state, occasion, and measurement error factors, using the steps below. These are based on the principles of path analysis, which are outlined in Plomin et al. [\(2008\)](#page-13-0). Figure [1](#page-4-0) shows the parameters used in this explanation.

Decomposing Observed Variables into State

and Measurement Error Components Variance (half-scale x at time $t = f_{tx}^2$ Variance (*State_t*) + Variance (e_{tx})

Percentage of variance in half-scale x at time t explained by the State factor = f_{tx}^2 Variance (*State_t*) / Variance (half-scale x at time t)

Percentage of variance in half-scale x at time t explained by measurement error = Variance (e_{tx}) / Variance (half-scale x at time t)

Decomposing State Factors into Trait and Occasion

Variance Variance (*State_t*) = Variance (*Trait*) + Variance (*Occ_t*)

Percentage of variance in State, explained by the Trait factor = Variance (*Trait*) / Variance (*State_t*)

Percentage of variance in State_t explained by the Occasion $factor = Variance (Occ_t) / Variance (State_t)$

Decomposing Occasion Factors into Autoregressive

and Disturbance Variance Variance $(Occ_t) = a_{t-1}²$ Variance (Occ_t) $_1$) + Variance (u_{t-1})

Percentage of variance in Occ_t explained by the previous Occasion factor (autoregressive effect) = a_{t-1}^2 Variance (Occ_{t-1}) / Variance (Occ_t)

Percentage of variance in Occ_t explained by new variance (disturbance factor) = Variance (u_{t-1}) / Variance (Occ_t)

Decomposing State Factors into Trait, Autoregressive,

and Disturbance Variance Variance (State_t) = Variance (Trait) + Variance (Occ_t)

Variance ($State_t$) = Variance ($Train$) + a_{t-1}^2 Variance (Occ_{t-1}) + Variance (u_{t-1})

Percentage of variance in State, explained by the Trait factor = Variance $(Train)$ / Variance $(State_t)$

Percentage of variance in State_t explained by the autoregressive effects = a_{t-1}^2 Variance (Occ_{t-1}) / Variance (State_t)

Percentage of variance in State_t explained by the disturbance factor = Variance (u_{t-1}) / Variance (*State_t*)

Decomposing Observed Variables into Trait,

Autoregressive, Disturbance, and Measurement Error

Components Variance (half-scale x at time t) = f_{tx}^2 ² Variance $(State_t) + Variance (e_{tx})$

Variance (half-scale x at time $t = f_{tx}^2$ Variance $(Trait) + f_{tx}^2 a_{t-1}^2$ Variance $(Occ_{t-1}) + f_{tx}^2$ Variance (u_{t-1}) + Variance (e_{tx})

Percentage of variance in half-scale x at time t explained by the Trait factor = f_{tx}^2 (Variance (*Trait*) / Variance (half-scale x at time t))

Percentage of variance in half-scale x at time t explained by autoregressive effects = $f_{tx}^2 (a_{t-1}^2 \text{ Variance} (Occ_{t-1}) / \text{Variance}$ (half-scale x at time t)

Percentage of variance in half-scale x at time t explained by the disturbance factor = f_{tx}^2 (Variance (u_{t-1}) / Variance (half-scale x at time t))

Percentage of variance in half-scale x at time t explained by measurement error = f_{tx}^2 (Variance (e_{tx}) / Variance (half-scale x at time t))

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