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Temporal ordering effects of adolescent depression, relational aggression, and victimization over six waves: Fully latent reciprocal effects models

The temporal ordering of depression, aggression, and victimization has important implications for theory, policy, and practice. For a representative sample of high school students (Grades 7–10; N 3,793) who completed the same psychometrically strong, multiitem scales 6 times over a 2-year period, there were reciprocal effects between relational-aggression and relational-victimization factors: aggression led to subsequent victimization and victimization led to subsequent aggression. After controlling for prior depression, aggression, and victimization, depression had a positive effect on subsequent victimization, but victimization had no effect on subsequent depression. Aggression neither affected nor was affected by depression. The results suggest that depression is a selection factor that leads to victimization, but that victimization has little or no effect on subsequent depression beyond what can be explained by the pre-existing depression. In support of developmental equilibrium, the results were consistent across the 6 waves.

Keywords: Relational aggression, victimization, depression, developmental equilibrium

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The focus of our study is on peer victimization (children and adolescents who are victims of aggression by their peers) and on aggression (perpetrators of aggressive, antisocial, and bullying behaviors). Peer victimization (i.e., being a victim of peer aggression) is damaging to children, having short- and long-term associations with physical and mental health and well-being (Bully Task Force, 2013; Marsh et al., 2011; Parada, Craven, & Marsh, 2008; Ryan & Smith, 2009; Rigby, 2007; Smith et al., 1999; Sullivan, 2000; Vassallo, Edwards, Renda, & Olsson, 2014). Systematic reviews (e.g., Farrington & Ttofi, 2009; Fox, Farrington, & Ttofi, 2012; Card, Stucky, Sawalani, & Little, 2008; Hawker & Boulton, 2000; Reijntjes, Kamphuis, Prinzie, & Telch, 2010; Takizawa, Maughan, & Arseneault, 2014) based largely on correlational data demonstrate that being a victim of peer aggression is associated with future criminality, long-term depression, and future violent behavior. For victims, repeated occurrences are associated with psychological distress, severe depression, psychopathology, and deteriorating physical health (e.g., Kaltiala-Heino, Rimpelä, Marttunen, Rimpelä, & Rantanen, 1999; Marsh, Parada, Craven, & Finger, 2004; Rigby, 1996; Sullivan, 2000). For example, Wolke, Copeland, Angold, and Costello (2013) found that adults who had been victims of aggression as children were more likely to have poorer health, to be less well-off, and to have poorer social relationships in adulthood, than those who were not victimized, even after adjusting for family and childhood risk factors. Using propensity score matching, Wong and Schonlau (2013) demonstrated that being a victim of childhood peer aggression was associated with delinquent behavior later in life.

Outcomes for aggressors are also dire (Card, 2011): increased risks of antisocial personality disorders in young adulthood (Wolke et al., 2013), later offending (Ttofi, Farrington, Lösel, & Loeber, 2011; Vassallo et al., 2014), and consequences for the peer group, school, and community. For example, in a prospective study, Janosz et al. (2008) showed that students who witnessed verbal and physical violence at school were more likely to be aggressive, disengaged with school, and truant. Hence, peer aggression results in socioeconomic costs, through its associated effects on criminality, depression, poor mental health, and poor school performance (Green, Collingwood, & Ross, 2010; Kass, 1999; Marsh et al., 2011; Olweus, 1991, 1993, 2013; Smith, 2014; Bully Task Force, 2013). Thus, the adverse effects of peer aggression are not confined to aggressors and victims, but are also felt by bystanders, and affect the school climate more generally.

Relational Aggression, Victimization, and Depression: Relations and Temporal Ordering

Peer Victimization and Depression

Correlations. Based on their recent meta-analysis, Wu, Zhang, Su, and Hu (2015; also see reviews by Card et al., 2008; Hawker & Boulton, 2000; Reijntjes et al., 2010) conclude that there is a positive relation between peer victimization and emotional maladjustment—such as internalizing problems and, more specifically, depression—the focus of the present investigation. However, Wu et al. (2015; also see Card et al., 2008) also note that whereas past research typically focused on an overt or an undifferentiated measure of victimization, recent research was more likely to consider different types of peer victimization, such as relational victimization, as in the present investigation. For the purposes of their review, and consistently with research in this area more generally, they distinguished overt victimization (physical and verbal) from relational victimization (e.g., social rejection, exclusion from social groups) and argued that relational victimization is likely to be more harmful. In related reviews, Reijntjes et al. (2010) and Card et al. (2008) make a similar distinction between what they refer to as direct and indirect forms of peer victimization. Of particular relevance to the present investigation, Wu et al. (2015) found that overt and relational victimization were both negatively associated with emotional adjustment, but that the associations were more negative for relational victimization.

Reciprocal effects models (REMs) of temporal ordering.

The negative correlations of relational victimization in particular, with depression and internalizing problems, show that victims of peer aggression suffer more emotional problems than do their classmates. However, as emphasized by Reijntjes et al. (2010) and many others (e.g., Leadbeater & Hoglund, 2009; Kochel, Miller, Updegraff, Ladd, & Kochenderfer-Ladd, 2012; Marsh et al., 2011), this relation does not address the issue of whether peer victimization is a cause or a consequence of emotional problems. Evidence in relation to temporal ordering typically is based on REMs of longitudinal data (e.g., Burkholder & Harlow, 2003; Guo, Marsh, Morin, Parker, & Kaur, 2015; Jöreskog, 1979; Little, Preacher, Selig, & Card, 2007; Marsh, Byrne, & Yeung, 1999; Marsh & Craven, 2006; Seaton, Marsh, Parker, Craven, & Yeung, 2015), in which each construct (see Figure 1; also see online supplemental materials for further discussion) is measured with multiitem scales (the boxes in Figure 1) and the same scales are collected in at least two and preferably three or more waves (T1, T2, and T3 in Figure 1). Critical questions of measurement invariance test whether the constructs are being measured in the same way in different waves (e.g., whether the factor structure is invari ant over time), and whether relations within each wave and across the different waves are consistent over time.

Although two measurement waves are required to test the temporal ordering in REMs, typically three or more waves are recommended (Little et al., 2007; Marsh et al., 1999; Marsh & Craven, 2006). In particular, at least three waves—and preferably more— are required to test developmental equilibrium assumptions that the effects of one variable on another across any two waves are consistent over multiple waves (e.g., Marshall, Parker, Ciarrochi, & Heaven, 2014; Parker, Marsh, Morin, Seaton, & Van Zanden, 2015). For example, in Figure 1 developmental equilibrium would require that the T1-depression ¡ T2-victimization path be the same as the T2-depression ¡ T3-victimization path. Support for developmental equilibrium is substantively important, showing that the relations among the constructs are stable even at the earliest ages considered in this sample. However, support for developmental equilibrium also facilitates interpretation of the results, providing a more parsimonious model and resulting in statistically stronger tests of a priori predictions (also see Little et al., 2007, for a more general discussion of assumptions in cross-lag panel studies).

Peer Victimization and Depression: Temporal Ordering in Four Theoretical Models

Four theoretical models of the temporal ordering of victimization and depression. Following reviews of empirical and theoretical research (e.g., Reijntjes et al., 2010; Leadbeater & Hoglund, 2009; Kochel et al., 2012), at least four models of relations between peer victimization and depression (see Figure 1) have been considered:

- Victimization does not equal Depression: a Stability Model (Leadbeater & Hoglund, 2009) or horizontal effects model in which all cross-lag paths are zero. In this “null” model, neither peer victimization nor depression is a cause or an effect of the other. (In Figure 1 the cross-paths, represented by the solid dark lines from depression to victimization factors, and the dashed lines, from victimization to depression factors, are all zero).
- Depression > Victimization: a symptoms-driven model (Kochel et al., 2012; Leadbeater & Hoglund, 2009). In this model of unidirectional causality, paths from depression to victimization (e.g., T1 Depression ¡ T2 Victimization) are posited to be significantly positive, while paths from victimization to depression are posited to be zero. This model posits that depression causes peer victimization, but that peer victimization does not lead to further depression.
- Victimization > Depression: an interpersonal risk model (Kochel et al., 2012) or victimization-driven model. In this model of unidirectional causality, paths from

victimization to depression (e.g., T1 Victimization ¡ T2 Depression) are positive, while paths from depression to victimization are posited to be zero. This model posits that peer victimization leads to depression, but that depression does not lead to peer victimization.

- Victimization <> Depression: a Reciprocal Effects Model (REM) or transactional model (Leadbeater & Hoglund, 2009; Kochel et al., 2012): In this bidirectional model of

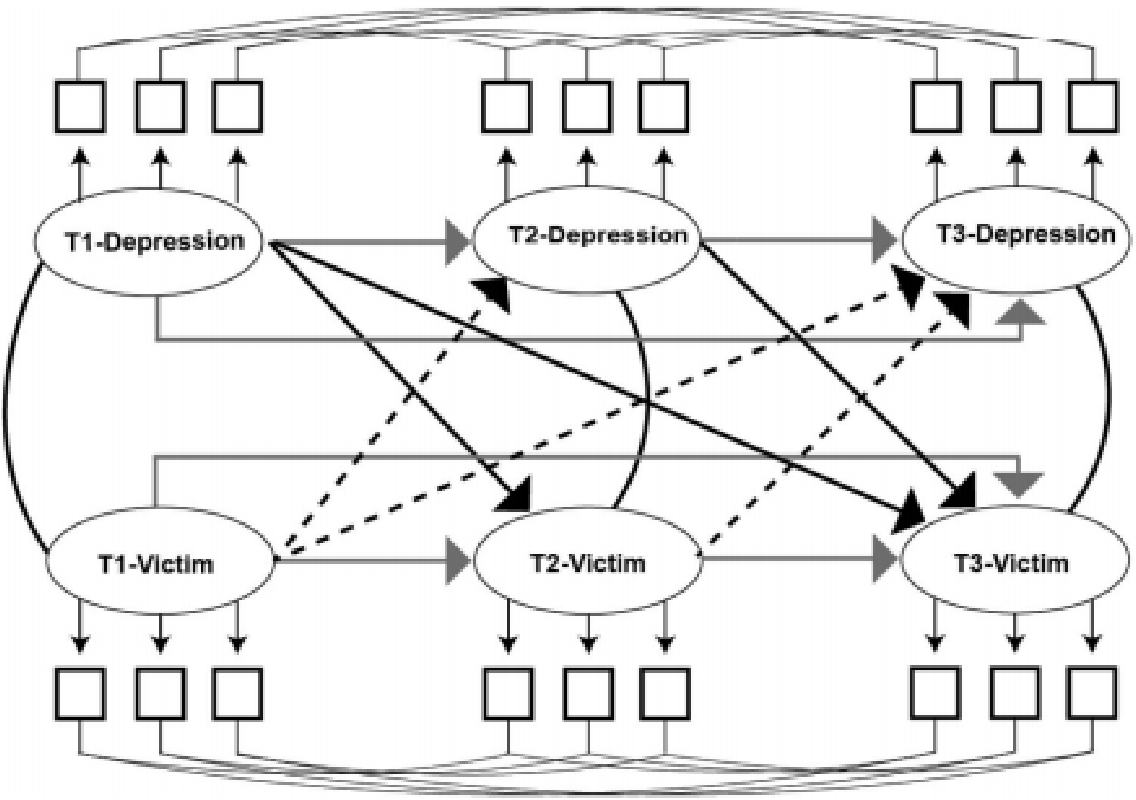

Figure 1. Prototypical reciprocal effects model of longitudinal relations between peer-victimization (Victim) and Depression. In this full-forward, multiwave, multivariable model, multiple indicators (items in the square boxes) of depression and victimization factors are collected in three successive waves (T1, T2, and T3). Each latent construct (represented by ovals) has paths leading to all latent constructs in subsequent waves. Within each wave, depression and victimization factors are assumed to be correlated; in the first wave, this correlation is a covariance between two latent constructs, and in subsequent waves, it is a covariance between residual factors. Curved lines at the top and bottom of the figure reflect correlated uniqueness between responses to the same measured variable (represented by boxes) collected on different occasions. Horizontal paths connecting the same variable on multiple occasions reflect stability (the solid gray paths), but these coefficients typically differ from the corresponding test–retest correlations (which do not include the effects of other variables). Dashed lines (cross-paths) reflect the effects of prior victimization on subsequent depression, whereas solid black lines (cross-paths) reflect the effects of prior depression on subsequent victimization. Developmental equilibrium tests whether the cross-paths over two adjacent waves (e.g., T1-depression → T2-victimization) are the same corresponding paths in subsequent waves (e.g., T2-depression → T3-victimization path). This basic model is easily adjusted to include more waves (which provide stronger tests of developmental equilibrium), more indicators of each construct (additional boxes), additional covariates (e.g., controlling for background variables), or additional constructs (i.e., multiple indicators of aggression measured at T1, T2, and T3 with corresponding stability paths, and cross-paths to and from depression and victimization factors over six waves of data—see Figure 2.)

causality peer victimization and depression are both a cause and an effect of each other. **Review of literature in relation to the four theoretical models.** In this section, we briefly review studies of relations between victimization and depression in relation to the four theoretical models of the temporal ordering of these constructs described above (also see Figure 1). We note that mere correlations between maladjustment and peer victimization are sometimes interpreted as consequences of peer victimization (a victimizationdriven model), but emphasize that such interpretations based on cross-sectional data are unwarranted.

Indeed, Wolke and colleagues (Woods, Wolke, Nowicki, & Hall, 2009; Wolke, Woods, & Samara, 2009; also see Guerra, Graham, & Tolan, 2011; Nowell, Brewton, & Goin-Kochel, 2014), found that physically or psychologically vulnerable children are more likely to become victims of aggression. Alluding to this problem, Paul and Cillessen (2003) suggested that internalizing behaviors and anxiety make children easy targets for aggression, "placing the child in a vicious cycle of victimization experiences from which it is difficult to escape" (p. 40). This suggests the possibility of a symptoms-driven model, or perhaps a reciprocal effects model, in which peer victimization and depression are mutually reinforcing. However, juxtaposing support for these various models requires stronger, longitudinal studies.

The Reijntjes et al. (2010) meta-analysis sought to evaluate linkages between peer victimization and internalizing problems, on the basis of prospective studies in which the same group of children were measured over two or more waves. Based on 18 longitudinal studies conducted between 1995 and 2006, they found support both for the effects of prior peer victimization on subsequent internalizing problems (controlling for prior internalizing problems), and the effects of prior internalizing problems on subsequent peer victimization (controlling for prior peer victimization). They reported that the effects were stronger for latent variable SEMs that controlled measurement error than for multiple regression models based on manifest variables, and when the same informants (typically self) were used to assess both constructs. In support of the reciprocal effects (transactional) model, Reijntjes et al. (p. 244). concluded that:

> Internalizing problems function as both antecedents and consequences of peer victimization. These reciprocal influences suggest a vicious cycle that contributes to the high stability of peer victimization.

Noting that most of the studies in their meta-analysis involved only two waves of data over a time span of less than 12 months, the authors called for more studies based on more waves of data collected over a longer period of time. They also emphasized that effects based on manifest models (e.g., multiple regression) are likely to be negatively biased. However, in relation to the criteria for REMs discussed earlier, it is important to emphasize that only two of the 18 studies in the Reijntjes et al. (2010) meta-analysis were based on latent-variable SEMs in which both peer victimization and internalizing behavior were measured with multiple indicators across all data waves; and apparently none of the studies controlled for complex models of measurement error, which are typical in longitudinal panel designs (Figure 1; see online supplemental materials for further discussion).

In a subsequent longitudinal path analysis, Taylor, Sullivan, and Kliewer (2013) found negative effects of T1 relational victimization— but not physical victimization— on T2 negative self-evaluations, which in turn led to T3 depression. Although the study was nominally longitudinal, because each of the measures was only reported at a single wave, it was not possible to evaluate the temporal ordering of depression with relational and physical victimization.

Takizawa et al. (2014) used a British cohort database to evaluate relations of being bullied at ages 7 and 11 (reported by parents) to diverse outcomes at ages 23 and 50. Controlling for childhood IQ (aged 11) and teacher reports of social adjustment (ages 7 and 11), victims were more likely to experience depression, anxiety, and suicidal ideation at ages 23 and 50. However, the effects were also significantly negative for subsequent social relations, economic well-being, and quality of life. Because the early measures of childhood depression were limited to behaviors observed by teachers the previous week, and because prevalence rates were low, there were no strong tests of being a victim on adult depression, and there were no tests of whether this victimization was a consequence of early depression. Nevertheless, the results attest to potentially long-lasting associations with being a victim of aggression.

Zwierzynska, Wolke, and Lereya (2013), based on logistic regression with manifest indicators, found positive effects of victimization in childhood on depression 4 years later, controlling for prior psychopathology and demographic factors. However, the authors noted that prior psychopathology at T1 was based on a dichotomous measure that lacked statistical power, due to low prevalence rate (4.3%), thus providing a weak basis for the evaluation of prior depression on subsequent victimization, or for controlling for prior depression.

Tran, Cole, and Weiss (2012) evaluated the longitudinal relations of peer victimization (relational and physical) and depression over two waves. Controlling for T1 measures, T1 depression had significant effects on both measures of victimization at T2, but T1 victimization had no significant effects on T2 depression. These results suggest support for a symptoms-driven model, qualified by the fact that their path model was based on manifest measures that failed to control for complex patterns of measurement error; this can greatly influence results based on REMs. Tran et al. also noted that they had considered only two waves of data, covering a single year, and suggested that more waves of data covering more than a single year should be considered.

In a stronger REM, Kochel, Ladd, and Rudolph (2012) evaluated relations between sociometric measures of peer acceptance, peer victimization (reports by self, peer, and teacher), and depressive symptoms (teacher and parent reports) measured at each of three time points (Grades 4, 5, and 6). Of particular relevance to the present investigation, prior depression was a significant predictor of subsequent victimization (controlling for prior victimization) from T1 to T2, and again from T2 to T3. In contrast, prior victimization had no significant effect on subsequent depression for either T1 ¡ T2 or T2 ¡ T3. Hence, the results support a systems-driven model, but not the victimization (interpersonal risk) model or even the transaction model of reciprocal effects. However, the authors also noted that the results might have differed had they used self-reports of depression, in that some depressive symptoms might be difficult to assess through adult informants (see De Los Reyes & Kazdin, 2005 for a review of discrepancies between informants and children’s self-reports of psychopathology).

Peer Aggression, Peer Victimization, and Depression

Card et al. (2011) note that a limitation of much existing research among school children is that the literatures on aggression and on victimization have progressed somewhat separately, with most scholars focusing on one aspect but not the other. Addressing this limitation is a major focus of the present investigation. Here we review relevant research on the associations between peer aggression, peer victimization, and depression.

Peer aggression and peer victimization: Positive relations. Historical models implicitly assuming that victimization and aggression factors represent endpoints of a bipolar continuum (implying a correlation approaching

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1.0 between the two) have been largely discredited (see discussion by Marsh et al., 2011). Indeed, a growing body of research from around the world (Harachi, Catalano, & Hawkins, 1999; Marsh et al., 2011; Roland & Idsøe, 2001; Smith et al., 1999; Sullivan, 2000) shows that aggression and victimization factors tend to be positively correlated with aggression. Based on longitudinal data, research suggests that these constructs may be mutually reinforcing, such that over time, aggressors tend to become victims and victims tend to become aggressors (Barker, Arseneault, Brendgen, Fontaine, & Maughan, 2008; Card & Hodges, 2008; Haltigan & Vaillancourt, 2014; Leadbeater & Hoglund, 2009; Marsh, Parada et al., 2004; Marsh, Parada, Yeung, & Healey, 2001; Ostrov, 2010; Parada, 2006; Fanti & Kimonis, 2012). These results have important implications for policy and research, suggesting that for either of these constructs, relations with subsequent outcome variables should not be considered in isolation of the other.

Peer aggression and maladjustment. Card et al. (2008) conducted a meta-analysis of 148 studies on relations between childhood aggression and various forms of maladjustment. The authors note there has been a historical shift from a focus on physical aggression to more nuanced forms of aggression, using terms such as indirect, covert, social, or relational aggression. In their review they distinguish between direct aggression (e.g., hitting, pushing, tripping, as well as verbal aggression such as name calling, taunting, or threatening) and indirect aggression (e.g., spreading gossip; excluding from groups or activities, often through indirect or covert means; threatening to terminate friendships). Card et al. recognized that each of these broad categories represented heterogeneous classes of behavior. (In the present investigation, the term relational aggression is used, rather than indirect aggression.) Even though the two forms of aggression are substantially correlated (mean r .76 in the Card et al. meta-analysis) there is support for their discriminant validity. In particular, boys had higher direct aggression scores than girls, while gender differences were trivial in size for relational aggression. Importantly, Card et al. found that direct aggression is related to externalizing problems, while (of particular relevance to the present investigation) relational aggression was more related to internalizing problems. Interestingly, Card et al. found that relations were not moderated by age or gender. In a subsequent meta-analysis of predictors of bullying and victimization, Cook, Williams, Guerra, Kim, and Sadek (2010) found that in adolescence particularly, internalizing and externalizing behaviors were both predictive of bullying and victimization. However, the effect of internalizing behaviors was a stronger predictor of victimization, while externalizing behaviors were a stronger predictor of being a bully.

Much research suggests the negative consequences of victimization in relation to depression (Hawker & Boulton, 2000; Schneider, O'Donnell, Stueve, & Coulter, 2012), but some research has also demonstrated positive correlations between aggression and depression (e.g., Angold, Costello, & Erkanli, 1999; Cook et al., 2010; Kovacs & Devlin, 1998). Indeed, Marsh et al. (2011; also see Bauman, Cross, & Walker, 2013) found that depression was positively related to victimization in particular but also, to a lesser extent, aggression. In a longitudinal study of bullying, Haltigan and Vaillancourt (2014) found that depression and psychopathology were associated with longitudinal trajectories of aggression and victimization, but did not relate these trajectories to changes in depression, nor test REMs of the temporal ordering of these constructs.

Longitudinal REM studies of peer victimization, peer aggression, and internalizing problems. Leadbeater and Hoglund (2009) evaluated links between physical aggression and depression (teacher reports), and peer victimization (self-reports) for young children at the start of Grade 1 (n 432; average age 6.3 years), with follow-ups at the end of Grades 1, 2, and 3. In an interesting variation of the latent variable REM described earlier, they tested a preliminary CFA measurement model and then used factor scores from this model as manifest variables in subsequent SEM path models. Coefficient alpha estimates of reliability were reasonable for the three constructs at all four measurement waves (.68 –.85). The fit of the measurement was reasonable, and supported the invariance of factor loadings over time (typically referred to as metric invariance or weak measurement invariance). Because this study included measures both of peer victimization and aggression, it was possible to test for relations between victimization and aggression. There was some support for a symptomsdriven model (depression ¡ victimization), but not for an interpersonal risk (victimization-driven) model, although this was not consistent across all time periods and alternative models. Interestingly, aggressive behaviors in Grade 2 led to increased victimization and internalizing in Grade 3. The authors suggested that, perhaps, early aggressive behavior increases risks of victimization, which then contributes to maintenance of aggression. Potential limitations of the study include the use of self-report measures for such young children, possible complex method effects, and only using teacher ratings of aggression and depression. Nonetheless, the implications are that early screening and interventions may be warranted for depressed and aggressive young children. Raising awareness of the risks of peer abuse in depressed children may serve to help them cope with peer victimization and feel safe at school.

Subsequently, Hoglund, and Chisholm (2014) evaluated REMs of linkages between peer aggression, peer victimization, peer exclusion, and internalizing problems (anxiety and depression) for young children in kindergarten to Grade 3, who were each assessed three times over the second half of a single school year. Peer aggression and exclusion were measured by peer nominations, while peer victimization and internalizing problems were measured by self-report. They found that prior internalizing problems were predictive of subsequent victimization, after controlling for prior victimization. However, in terms of the effect of prior victimization on subsequent internalizing problems (no effects between Waves 1 and 2, but small positive effects between Waves 2 and 3), they had mixed results. In support of an internalizing risk model they found that children who were initially aggressive became victims of peer exclusion: this led to increased internalizing problems, whereas children who showed more internalizing problems became victims of peer victimization and exclusion. Surprisingly, neither the Leadbeater and Hoglund (2009) nor the Hoglund and

Chisholm (2014) studies reported tests of the path from prior internalizing problems to subsequent aggression, even though these constructs tended to be positively correlated.

The Present Investigation

Our study is a substantive-methodological synergy, applying strong methodology to address substantively important issues with theoretical and policy-practice implications (Marsh & Hau, 2007). The substantive issue is the attempt to disentangle the temporal ordering of relational-aggression, relational-victimization, and depression during adolescence, on the basis of an analysis of six waves of responses (N 3,793 high school students) collected at 4-month intervals (near the start, at the middle, and near the end of each school year) over a 2-year period. Methodologically, the study uses fully latent REMs, based on psychometrically strong measures (see Marsh et al., 2011).

Research Hypotheses and Research Questions

Hypothesis 1: Correlations. Consistently with previous research, relational-aggression, relational-victimization, and de pression factors are hypothesized to be positively correlated within each of the six waves of longitudinal data.

Hypothesis 2: Path coefficients in the temporal ordering model (see Figure 2). Hypothesis 2a: Aggression and victimization. Aggression and victimization are hypothesized to be positively and reciprocally related (see Figure 2). This pattern of predicted relations is hypothesized to be consistent across the six waves of data.

Hypothesis 2b: Depression and victimization. Based on previous theory and on limited research (e.g., Paul & Cillessen, 2003; Reijntjes et al., 2010), depression and victimization are hypothesized to be reciprocally related. This pattern of predicted relations is hypothesized to be consistent across the six waves of data.

Hypothesis 2c: Depression and aggression. As there is no clear research, nor, apparently, a theoretical basis for positing the temporal ordering of relations between depression and aggression, we leave this as a research question and posit no paths between these two variables. However, particularly as there is evidence suggesting a positive correlation between these two constructs (as predicted in Hypothesis 1), paths representing the reciprocal effects between these two constructs (i.e., from prior aggression to subsequent depression and from prior depression to subsequent aggression) are evaluated.

Hypothesis 3: Robustness of path coefficients.

Hypothesis 3a: Developmental equilibrium. In support of developmental equilibrium, based on tests of the invariance of paths in the REM across the six waves, paths in support of Hypotheses 2a, 2b, and 2c are hypothesized to be invariant across the multiple waves (wavei

¡ wavei 1 for i 1 to 5). Support for this hypothesis is substantively important, suggesting that the relation between aggression and depression is in a stable state by the earliest ages measured in the sample.

Hypothesis 3b: The robustness of the results is also tested, by evaluating whether controlling for background variables (gender, year-in-school, and their interaction) changes the interpretation of the results. However, it is posited that the inclusion of covariates will have little or no effect on the pattern of statistical significance and on the size of the REM path coefficients associated with the aggression, victimization, and depression factors, which are the main focus of the study.

Method

Participants and Materials

The eight schools participating in the present investigation were drawn from high schools affiliated with a large Catholic Education Office in metropolitan Sydney, Australia. Participants (N 3,793 students) were in Years 7 to 10 at the time of the first data collection (Mn Age 13.7, SD 1.4; 42% males, 86% Australian born; mainly middle- and working-class families). The questionnaires were administered to all students on six, evenly spaced occasions over a 2-year period. Study procedures and assessments were approved by ethics boards at the Western Sydney University and the Catholic Education Office, Diocese of Parramatta. Informed parental consent and participant assent were obtained before participation in the study.

Considered here are responses to the relational aggression and victimization scales from the Adolescent Peer Relations Instrument (Marsh et al., 2011; Marsh, Parada et al., 2004; Parada, 2006). For the relational-aggression items, students were asked to state how often, on a 6-point Likert scale (1 Never to 6 Every day), they had engaged in a series of behaviors against other students (Got my friends to turn against a student; Told my friends things about a student to get them into trouble; Got other students to start a rumor about a student; Got other students to ignore a student; Left them out of activities or games on purpose). For the relational-victimization items, students were asked how often these behaviors had occurred to them (A student wouldn’t be friends with me because other people didn’t like me; A student ignored me when they were with their friends; A student got their friends to turn against me; I was not invited to a student’s place because other people didn’t like me; A student got students to start a rumor about me; I was left out of activities, games on purpose). In each of the six waves, the coefficient alpha estimates of reliability for these two scales were greater than .85. Depressive symptoms— cognitive and behavioral markers of depression—were measured with the short (10-item) version of the widely used Child Depression Inventory (CDI, Kovacs, 1992). The factor structure of the aggression, victimization, and depression measures was considered as part of the present investigation (also see online supplemental materials, Table 1).

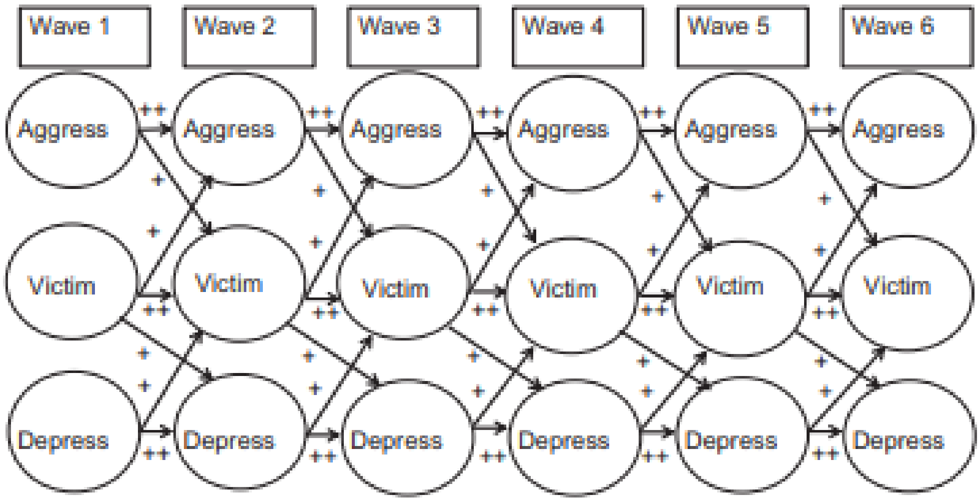

Figure 2. A priori predictions for Lag-1 paths. All bold black paths are predicted to be statistically significant (++ or +). No a priori predictions were made for the paths from Aggression to Depression, but these were included in the model as research questions. Consistent with the assumption of developmental equilibrium, all paths are predicted to be invariant over the multiple waves.

Statistical Analyses

All our analyses were done with Mplus (Muthén & Muthén, 2008 –2014, Version 7). For all models, all latent factors were estimated from multiple items. The instruments were administered on six occasions during a 2-year period of time. As is typical in large longitudinal field studies, a substantial portion of the sample had missing data for at least one of the six occasions, due primarily to changing schools, to absence, or to an illegible (or fictitious) name being supplied on at least one of the six occasions. For the sample of 3,793 students, the number of waves of data completed by each student was: 1 (8.2%), 2 (11.6%), 3 (19.0%), 4 (13.0%), 5 (21.6%) and 6 (26.5%). Not surprisingly, missing data were consistent across variables, in that missingness was largely a function of the wave, rather than the variable. That is, there was very little missing data within a wave for students participating in that wave. For present purposes we used multiple imputation in relation to missing data, because this allowed us to use a consistent data set for a wide variety of models based on different variables, and not based on any one of the many models that we considered and to incorporate more easily auxiliary variables (e.g., gender, age, year in school, number of waves of data completed, home language, ethnicity, and country of birth of the student and each of their parents); see online supplemental materials Section 3 for further discussion. All models were fitted using the robust Maximum Likelihood estimator (MLR) in combination with the complex design available in Mplus, to account for the nesting of students within schools. Based on all variables considered in the present investigation (all the victimization, aggression, and depression items plus gender, age, year in school, number of waves of data completed, home language, year in school, ethnicity, country of birth), the Mplus multiple imputation procedures (MCMC algorithm with Bayes estimator using the default convergence) were used to handle the missing data. Subsequent analyses were done on five imputed data sets, and the results were combined automatically in Mplus using the Rubin (1987; Schafer, 1997) strategy to obtain unbiased parameter estimates, standard errors, and goodness of fit statistics.

Preliminary Analyses: Technical Issues in the Selection of the Most Appropriate Model

Critical to the present investigation are tests of the factor structure underlying our measures, the invariance of parameter estimates across the six waves, and the goodness of fit of competing models in the selection of the most appropriate model. Although these issues are critically important, and typically have been neglected in previous research in this area, here we treated these as preliminary analyses that underpin the central substantive questions: the temporal ordering of depression, relational-victimization, and relational-aggression. In the models summarized in Table 1 (also see online supplemental materials for syntax from selected models) the set of CFA models tested proceeded from no longitudinal constraints, to the addition of correlated

Table 1

Goodness of Fit for Alternative Cohort-Sequence Models: Bully, Victimization, Depression

Model	ChiSq	DF	RMSEA	CFI	TLI	Description
			Confirmatory Factor Analyses (CFAs)			
CFA1	17235	8361	.017	.926	.924	No Invariance; No Correlated Uniquenesses (CUs)
CFA2	11401	8031	.011	.971	.970	CFA1 + CUs
CFA3	11586	8126	.011	.971	.970	CFA2 + Factor loadings invariant over waves[a]
			Confirmatory Factor Analyses (CFAs) + Year-in-school (Yr), Gender (G), Year-by-gender (YR × G)			
CFA4	12384	8468	.011	.968	.966	CFA3 + + Gender, Age, YR × G corrs
			Structural Equation Model (SEMs)			
SEM1	12670	8216	.012	.963	.961	CFA2 with noninvariant Lag 1 path coefficients
SEM2[a]	12885	8252	.012	.962	.960	SEM1 + path coefficients invariant over waves
SEM3	11643	8186	.011	.971	.970	SEM1 + noninvariant a priori paths[b]
SEM4[a]	12126	8240	.011	.968	.966	SEM3 + invariant a priori paths[b]
			Structural Equation Model (SEMs) + Year-in-school, Gender, Year-by-gender (YR × G)			
SEM5	13217	8627	.012	.963	.961	SEM3 + Year, Gender, YR × G (T1 paths only)
SEM6	13024	8618	.012	.964	.962	SEM3 + Year, Gender, YR × G (T1–T2 paths)
SEM7	12711	8582	.011	.965	.963	SEM3 + Year, Gender, YR × G (T1–T6 paths)

Note. ChiSq = chi-square; DF = degrees of freedom ratio; CFI = Comparative fit index; TLI = Tucker-Lewis index; RMSEA = Root mean square error of approximation. CUs = a priori correlated uniquenesses for same items presented on multiple waves. FL = factor loadings. Mplus syntax for selected models is presented in the online supplemental materials.

[a] Path coefficients, as well as factor loadings, are constrained to be equal across the six waves of data. [b] A priori path coefficients include all test–retest stability paths relating measures of the same construct from different waves (i.e., Lag 1 to Lag 5 paths for Wave 6 factors), but only Lag 1 cross-paths relating different constructs.

errors, to a model with both constrained factor loadings and path coefficients. In this section we briefly review some of the statistical issues underlying these models, as well as some preliminary results underpinning the substantive focus of our research.

Tests of measurement invariance evaluate the extent to which measurement properties generalize over multiple groups, situations, or occasions. Of particular substantive importance for educational and developmental research based on longitudinal data is the evaluation of differences over time, in that, unless the underlying factors are measuring the same construct in the same way, and the measurements themselves are operating in the same manner across time, the comparison of parameter estimates is potentially invalid. A distinctive feature of longitudinal data is the complex structure of measurement error, which is likely to bias estimates based on manifest measures (i.e., responses to scale scores or single-item responses), rather than on fully latent REMs, which are based on responses to individual items, such as those considered here.

For the present purposes, the main substantive interest is the effects of the three latent constructs (aggression, victimization, and depression factors) on the same variables in the subsequent waves (see Research Hypotheses 2a–2c), hereafter referred to as "Lag 1" paths. However, also included in the a priori path model were paths leading from the same variable collected in earlier data waves. Thus, for example, victimization in Wave 6 was predicted by aggression, victimization, and depression factors from Wave 5 (Lag 1 variables), but also by victimization factors from Waves 1– 4 (Lag 2–5) variables. The model is conservative in that it shows the effects of nonmatching variables (e.g., the effects of aggression on victimization, controlling for prior victimization), particularly compared to studies that include only two or perhaps three waves of data. Although the a priori model considered here includes these test–retest stability paths from all waves, models positing only Lag 1 paths were also evaluated, to determine whether support for a priori hypotheses depends on this methodological feature. Although this was not a major focus of the present investigation, the robustness of the parameter estimates was also evaluated, in relation to models that included gender, year in school, and their interaction, as covariates in the REMs. Below we briefly summarize the preliminary analyses leading to the selection of the most appropriate latent variable (CFA and SEM) models used to test a priori hypotheses, starting with a brief discussion of goodness of fit.

Goodness of fit. Due to the known sensitivity of the chisquare test to sample size, to minor deviations from multivariate normality, and to minor misspecifications, applied SEM research focuses on indices that are sample-size independent (Hu & Bentler, 1999; Marsh, Balla, & McDonald, 1988; Marsh, Balla, & Hau, 1996; Marsh, Hau, & Wen, 2004; Marsh, Hau, & Grayson, 2005), such as the Root Mean Square Error of Approximation (RMSEA), the Tucker-Lewis Index (TLI), and the Comparative Fit Index (CFI). Population values of TLI and CFI vary along a 0 –1 continuum, in which values greater than .90 and .95 typically reflect acceptable and excellent fits to the data, respectively. Values smaller than .08 and .06 for the RMSEA support acceptable and good model fits, respectively. The chi-square difference test can be used to compare two nested models, but this approach suffers from even more problems than does the chi-square test for single models—problems that led to the development of other fit indices (see Marsh et al., 2005). Cheung and Rensvold (2001) and Chen (2007) suggested that if the decrease in fit for the more parsimonious model is less than .01 for incremental fit indices such as the CFI, there is reasonable support for the more parsimonious model. For indices that incorporate a penalty for lack of parsimony, such as the RMSEA and the TLI, it is also possible for a more restrictive model to result in a better fit than would a less restrictive model. However, it is emphasized that these cut-off values constitute rough guidelines only, rather than “golden rules” (Marsh, Hau et al., 2004).

Standardized metric. There is no clearly agreed-upon approach to the standardization of parameter estimates in fully latent models of longitudinal data and the traditional approach for crosssectional data (e.g., standardizing each latent variable to have SD 1) might not be appropriate for longitudinal data, in which the SDs for the same construct might vary over time. In order to identify the models, the traditional approach of fixing the first factor loading for each factor to 1.0 was used. However, to provide parameter estimates standardized to a common metric over the multiple waves, in a preliminary CFA, factor loadings were constrained to be invariant over the multiple waves (typically referred to as metric invariance or weak measurement invariance), and the metric was identified by fixing to 1.0 the factor variances of constructs measured in Wave 1, instead of fixing the first factor loading to 1.0. In subsequent SEMs these standardized factor loadings were used to define the latent factors, fixing the first factor loading for each factor to the value obtained in the CFA, in which the factor variances were fixed to be 1.0. In this way, parameter estimates were estimated in relation to a standardized metric based on SDs in Wave 1, a metric that was common across the six waves (see online supplemental materials for syntax).

CFA factor structure: Correlated uniquenesses. In preliminary analyses CFA was used to test the factor structure underlying responses to the 132 items (six aggression items, six victimization items, and 10 depression items for each of six waves of data) and their relation to gender and year in school. In longitudinal analyses in which the same items are administered across multiple waves, it is critical to incorporate a priori correlated uniquenesses (i.e., estimated correlations between item residuals) relating responses to the same items across multiple waves (Jöreskog, 1979; Marsh & Hau, 1996; Marsh, Lüdtke, Nagengast, Morin, & Von Davier, 2013). Failure to include them is likely to result in a poor fitting model and in positively biased parameter estimates of stability over time. Positively biased estimates of stability in turn are likely to result in negatively biased estimates of the effects of other variables leading to that construct. At its extreme, the failure to include correlated uniqueness can result in such positively biased estimates of stability that standardized stability coefficients approach or even exceed 1.0 (e.g., Marsh, Martin, & Debus, 2001). In support of their inclusion, model CFA2 (see Table 1) with correlated uniquenesses relating responses to the same item across all waves, fitted the data (CFI .971, TLI .970) substantially better than did model CFA1 (see Table 1) without correlated   uniquenesses (CFI .926, TLI .924); the difference in fit (CFI .045, TLI .046) is large, relative to suggested guidelines (e.g., CFI .01). Hence, correlated uniquenesses are included in all subsequent models.

CFA factor structure: Factor loading invariance. In support of factor loading invariance (i.e., metric invariance), the goodness of fit indices were similar for model CFA3 (factor loadings invariant over waves; CFI .971, TLI .970) and model CFA2 (factor loadings not invariant; CFI .971, TLI .970). Finally, in model CFA4, gender, year, and school were added to the model, to evaluate the effects of gender and age. In the final model, with factor loadings invariant over waves (see online supplemental materials); factor loadings relating each item to its corresponding latent factor were all statistically significant and substantial. A latent correlation matrix based on this final CFA model was used to test Hypothesis 1, about relations among aggression, victimization, and depression factors (see subsequent discussion in the Results section).

SEM path coefficients: Lagged effects. In the most parsimonious REM models, only Lag 1 paths are included (i.e., only paths from one wave to the next), but a more conservative approach is to include test-retest stability paths for all waves (this approach hereafter referred to as the "a priori path model"). Also, particularly for models with many waves, constraining the paths to be invariant over waves provides a test of developmental equilibrium assumption, greatly facilitates interpretation of the results, and results in more robust, precise estimates. Models SEM1–SEM4 evaluate all four combinations of these possibilities.

Models with only Lag 1 paths (SEM1 and SEM2 in Table 1) provide a somewhat poorer fit to the data than do the a priori path models (with all stability paths, SEM3 and SEM4), but the difference in fit is small (CFI and TLI .01). However, not surprisingly, test–rest stability coefficients were substantially larger for Model SEM2, which contained only Lag 1 paths (.484 –.591), than for model SEM4, which contained all stability paths (.398 – .491). Hence, at least some of the variance in each outcome could be predicted by previous measures of the same variable that were collected prior to the Lag 1 measure.

Invariance of path coefficients: Developmental equilibrium (Hypothesis 3a). It is useful to evaluate the invariance of relations among individual difference variables in SEMs of longitudinal data. Test–retest stability refers to the size of the test-retest (or autoregressive) paths for the same variable for two or more waves (e.g., aggression wavei ¡ aggression in wavei1 where i 1 to 5). These test–retest paths are said to be invariant when Lag 1 paths are equal over multiple waves (e.g., aggression wavei ¡ aggression wavei1 aggression wavei1 ¡ aggression wavei2, assuming equal length intervals; Kenny, 1979). In the final model (SEM4), second-to-fourth autoregressive paths were constrained to be equal over time (e.g., aggression wave1 ¡ aggression wave5 aggression wave2 ¡ aggression wave6). Particularly relevant for REMs, developmental equilibrium refers to the invariance over waves of cross-paths from a variable in one wave to another variable in the next wave (e.g., aggression wavei ¡ victimization wavei1 aggression wavei1 ¡ victimizationi2 aggression in wavei). Developmental equilibrium has a number of important advantages that make it attractive, methodologically and substantively (see earlier discussion). In support of developmental equilibrium (Hypothesis 3a), the difference in fit for models constraining these path coefficients to be equal over time is small (SEM1 vs. SEM2: CFI .001, TLI .001, RMSEA .000; SEM3 vs. SEM4: CFI .003, TLI .004, RMSEA .000). In summary, the final latent model (SEM4) resulted in an excellent fit to the data (CFI .968, TLI .966, RMSEA .011) and provided the basis of subsequent results used to test a priori hypotheses.

Results

Tests of a Priori Hypothesis 1: Relations Among Constructs

Of particular interest, and in support of Hypothesis 1, aggression, victimization, and depression factors were consistently correlated positively in each of the six waves (see Table 2), and all correlations were statistically significant. Within each of the six waves, correlations between aggression and victimization factors varied from .269 to .429, while depression was positively related to aggression factors (.105 to .182) and particularly to victimization factors (.416 to .438). Although gender was not a major focus of the present investigation, female students had significantly higher depression scores and significantly lower aggression and victimization scores. Particularly in the first wave of data, year in school was positively related to all three factors, but gender-byyear interactions were nonsignificant for all six waves of data. These results support Hypothesis 1, in which relational-aggression, relational-victimization, and depression factors are hypothesized to be positively correlated within each of the six waves of longitudinal data.

Tests of A Priori Hypotheses of the Temporal Ordering of Aggression, Victimization, and Depression: The REM Paths (see Table 3 and Figure 2)

Victimization and aggression (Hypothesis 2a). Consistently with predictions, and across the six waves, there is a clear pattern of reciprocal positive effects relating the aggression and victimization factors. Aggression in each wave had a significantly positive effect on victimization in the next wave, and victimization in each wave had a significantly positive effect on aggression in the next wave. Hence, aggression and victimization are reciprocally related.

Depression and victimization (Hypothesis 2b). Here the results are only partially consistent with a priori predictions. Consistently with predictions across the six waves, prior depression had a significant effect on subsequent victimization. However, the effect of prior victimization on subsequent depression is nonsignificant. Hence, in contrast to the prediction of reciprocal effects, the ordering of effects is unidirectional (depression ¡ victimization), suggesting that the widely cited correlation between victimization and depression reflects mostly the predictive effect of prior depression on victimization, rather than any substantial predictive effect of prior victimization on subsequent depression that is implicit in much discussion of this relation. Thus, depression appears to be a selection factor that leads to victimization, but victimization has little predictive effect on subsequent depression, beyond that explained by the victim's preexisting depression.

Table 2
Correlations Among Latent Variables

	WAVE 1			WAVE 2			WAVE 3			WAVE 4			WAVE 5			WAVE 6		
	W1A	W1V	W1D	W2A	W2V	W2D	W3A	W3V	W3D	W4A	W4V	W4D	W5A	W5V	W5D	W6A	W6V	W6D
Latent Factors																		
Wave 1																		
W1AGR	1.00																	
W1VIC	.269	1.00																
W1DEP	.129	.437	1.00															
Wave 2																		
W2AGR	.529	.191	.105	1.00														
W2VIC	.175	.544	.283	.290	1.00													
W2DEP	.090	.259	.606	.163	.419	1.00												
Wave 3																		
W3AGR	.441	.143	.050	.537	.164	.070	1.00											
W3VIC	.154	.446	.254	.206	.598	.314	.275	1.00										
W3DEP	.079	.213	.479	.105	.299	.630	.105	.438	1.00									
Wave 4																		
W4AGR	.319	.120	.082	.405	.143	.066	.458	.170	.091	1.00								
W4VIC	.116	.302	.191	.171	.440	.251	.177	.485	.247	.344	1.00							
W4DEP	.058	.206	.388	.073	.263	.461	.057	.273	.537	.133	.425	1.00						
Wave 5																		
W5AGR	.277	.139	.074	.334	.135	.056	.414	.175	.057	.519	.265	.083	1.00					
W5VIC	.086	.273	.150	.132	.347	.196	.129	.399	.250	.217	.494	.293	.376	1.00				
W5DEP	.065	.145	.297	.099	.210	.375	.082	.232	.436	.127	.277	.582	.178	.438	1.00			
Wave 6																		
W6AGR	.232	.117	.034	.295	.155	.039	.341	.172	.056	.425	.212	.072	.496	.266	.120	1.00		
W6VIC	.089	.243	.107	.116	.332	.160	.122	.361	.174	.155	.408	.190	.223	.493	.235	.429	1.00	
W6DEP	.030	.137	.279	.062	.178	.345	.070	.196	.379	.090	.224	.475	.077	.281	.571	.182	.416	1.00
Demographic Variables																		
Gender	−.235	−.115	.117	−.247	−.107	.118	−.223	−.138	.100	−.173	−.125	.106	−.206	−.088	.078	−.180	−.102	.081
Year	.242	.103	.118	.153	−.009	.070	.074	−.058	.042	.073	−.009	.054	.065	−.010	.082	.024	−.040	.015
YR × Gender	−.057	−.017	.063	−.024	−.015	.049	−.006	.009	.036	.011	.011	−.031	.007	−.032	.005	.027	.009	.015

Note. W1–W6 = Wave 1 to Wave 6 (six occasions over a 2-year period). AGR = Aggression; VIC = Victimization; DEP = Depression. Gender (male = 1, female = 2). Year (Yr) = year in school. YR × Gender = year-by-gender interaction. All correlations that are not statistically significant are shaded in gray. (See online supplemental materials for factor loadings.)

Table 3
Reciprocal Effect Model Paths Based on Selected Models (See Table 1)

Model	Outcome Variables (To Wave$_{i+1}$)		
	Aggression W_{i+1}	Victimization W_{i+1}	Depression W_{i+1}
Predictor (From Wave i)	UnStd/SE(Std)	UnStd/SE(Std)	UnStd/SE(Std)
SEM2 (Path coefficients invariant over waves; only Lag 1 paths estimated)			
Aggression W_i	.509/.030 (.509)	.041/.019 (.028)	.000/.003 (.001)
Victimization W_i	.041/.014 (.060)	.484/.022 (.484)	.007/.005 (.027)
Depression W_i	−.011/.035 (−.005)	.163/.026 (.045)	.591/.032 (.591)
SEM4 (A priori paths invariant over waves)			
Aggression Wi	.398/.025 (.398)	.040/.018 (.027)	.001/.003 (.003)
Victimization W_i	.043/.013 (.064)	.397/.013 (.397)	.008/.005 (.028)
Depression W_i	−.014/.036 (.006)	.134/.026 (.038)	.491/.027 (.491)
SEM5 (SEM4 + Covariates: Gender, Year-in-School, YR × Gender; Lag 1 paths only)			
Outcomes			
Aggression W_i	.400/.025 (.400)	.039/.018 (.027)	.001/.003 (.003)
Victimization W_i	.044/.013 (.065)	.398/.013 (.398)	.007/.005 (.027)
Depression W_i	−.020/.037 (−.008)	.129/.026 (.036)	.492/.026 (.492)
Covariates[a]			
Gender W_1	−.162/.030 (−.244)	−.117/.036 (−.120)	.035/.005 (.129)
Year-in-School W_1	.162/.020 (.244)	.093/.017 (.096)	.033/.005 (.121)
YR × Gender W_1	−.039/.011 (−.059)	−.018/.016 (−.018)	.017/.007 (.062)

Note. Path coefficients relate predictor variables at each wave to outcome variables at the next wave: i.e., Lag 1 path coefficients relate predictors at wave (Wave$_i$ = W_i) to outcomes at wave (Wave$_{i+1}$ = W_{i+1}). UnStd = Unstandardized path coefficients; *SE* (Standard Error); path coefficients more than twice their standard error are statistically significant at $p < .05$; Std = path coefficients standardized to a common metric.
[a] These covariates are constant over time, and paths refer to the effects of covariates on Wave 1 outcomes.

Depression and aggression (Research question 2c). Across the six waves, paths were nonsignificant from prior aggression to subsequent depression and from prior depression to subsequent aggression. Hence, prior aggression has no predictive effect on subsequent depression and prior depression has no predictive effect on subsequent aggression.

Developmental equilibrium (Hypothesis 3a). Consistently with the developmental equilibrium hypothesis, Model SEM4 (Table 1; also see Table 3) with all REM paths invariant over waves is supported. The goodness of fit of Model SEM4 is good (CFI .968, TLI .966), and the difference in fit of the corresponding SEM3 without invariant paths is small (CFI .003, TLI .004).

Robustness of REM effects (Hypothesis 3b). Does controlling for covariates (gender, year in school, and their interaction) alter the pattern of paths? This issue is evaluated in relation to a set of three SEMs, multiple-indicator-multiple-cause (MIMIC) models that test the effects of these covariates on outcomes (aggression, victimization, depression) at Wave 1 (SEM5), Waves 1 and 2 (SEM6) and Waves 1 through 6 (SEM7). The goodness of fit for the three models suggests that SEM5 (see Table 3) provides an acceptable fit to the data (CFI .963, TLI .961) and that the addition of paths to subsequent waves had a minimal effect on goodness of fit (CFI and TLI .002). Although gender is not a major focus of this study, the results (Model SEM5 in Table 3) again showed that girls have significantly lower scores for aggression and victimization factors, but significantly higher depression scores. Year in school is positively related to aggression, victimization, and depression factors. However, there are also small but statistically significant interactions, such that gender differences in aggression and depression are smaller for older students. The critical issue, for the purposes of the present investigation and for Hypothesis 3b, is whether controlling for these covariates has a significant effect on paths relating aggression, victimization, and depression outcome factors (Model SEM5 in Table 3). Inspection of the results indicates that the pattern of statistical significance is the same, and that the actual parameter estimates are nearly unchanged in Models SEM5–SEM7, compared to those in Model SEM4.

Discussion

A Substantive-Methodological Synergy

Our study is a substantive-methodological synergy, applying stronger methodology than typically used in this area of research to address substantively important issues with implications for theory and practice. Substantively, we evaluated the temporal ordering of depression, aggression, and victimization across six waves of data in relation to theoretical models of these relations. In support of a symptoms-driven model, after controlling for prior depression, aggression and victimization—as well as gender, age, and their interaction—depression had a positive predictive effect on subsequent victimization, but victimization had no significant effect on subsequent depression. In contrast, aggression neither affected nor was affected by depression. However, aggression and victimization were reciprocally related, such that victims became aggressors and aggressors became victims. In support of the developmental equilibrium hypothesis, these patterns of results were consistent over six waves of data for this sample of high school students. Methodologically, we provided guidelines in relation to measurement and statistical models that were a basis of our evaluation of previous research and recommendations for future research. Our results have implications for theory, in that at least implicit in much previous research is the assumption that victimization leads to subsequent depression. Of importance to both theory and practice is the finding that depression is apparently a selection factor: that aggressors target students who are depressed. This finding also has important implications for school interventions, such as the need for early identification of depressed students at school as they may fall victims to aggressors due to their depression, helping depressed and vulnerable students to cope with victimization by standing up for themselves, avoiding aggressors, and seeking help from peers and school staff, and for schools to improve the school climate in support of these students (Leadbeater & Hoglund, 2009). Our findings also suggest that individual treatment for depressed students should include strategies on how to manage victimization (such as seeking support), or at the very least clinicians should regularly check with their patients if they are being victimized even if this was not the main presenting problem at the time treatment was initiated. Although possibly counterintuitive, this finding is consistent with previous research that has shown physically and psychologically vulnerable students are more likely to be the targets of aggression (e.g., Woods et al., 2009; Wolke et al., 2009); depression is clearly a source of vulnerability. Although many studies have considered different sources of vulnerability as victim selection factors, more research is needed to juxtapose multiple sources of physical, social, and psychological vulnerability or, perhaps, merely being different.

Strengths and Limitation of the Present Investigation

A number of strengths of the present investigation support the robustness of the findings. Theoretically, we systematically reviewed the current literature in relation to four theoretical models of relations between depression, aggression, and victimization, identifying strengths and particularly limitations of current research—some of which we were able to address in the current investigation. Empirically, we began with psychometrically strong measures, demonstrating support for the a priori factor structure underpinning these measures and the invariance of the factor loadings over the six waves of data. We contrasted results based on competing latent-variable models of these longitudinal data that provided empirical tests of theoretical models posited in this research literature. We demonstrated support for the developmental equilibrium hypothesis, showing that that the pattern of relations among these constructs and support for their temporal ordering was consistent across the six waves. Also of importance was the finding that controlling for key covariates (gender, year in school, and their interaction) had little or no effect on the pattern of results.

Clearly it is premature to conclude on the basis of this one study, that victimization has no effect on subsequent depression, even if the results are consistent with this hypothesized model. Indeed, the more important conclusion is that there is clear support, consistent with a limited number of other studies reviewed earlier, that depression is a characteristic that aggressors use to select victims. Nevertheless, tests of the generalizability of the results to other student populations, school types, and age groups are clearly warranted.

It is also relevant to consider a wider range of outcome variables, including other forms of aggression (e.g., physical aggression) as well as other indicators of emotional maladjustment (e.g., other internalizing problems such as anxiety, as well as externalizing problems). Although the pattern of cross-paths in the REMs considered here was robust in relation to statistical significance, developmental equilibrium, and the control of critical covariates, the sizes of the effects were not large. Whereas the inclusion of six waves of data is clearly a strength, there is also need for further research about the timing and number of measurement points. While there are also limitations in reliance on selfreport, we also conjecture that self-reports might be the most valid way to infer student self-perceptions in relation to these constructs so that it would also be useful to include—in addition to selfreports—responses from multiple informants. Also, as with most research into victimization, the focus of the present investigation was on the negative psychological consequences, rather than on factors that increase resiliency to victimization (see Reijntjes et al., 2010).

We also note that while REMs provide much stronger tests of temporal ordering than do mere correlations based on crosssectional data, the results are still correlational. Thus, while it is appropriate to hypothesize the temporal ordering of effects and to evaluate models of temporal ordering, the support for such a priori hypotheses is only in the form of empirical evidence that is consistent with the hypotheses, and does not rule out alternative interpretations of the findings. For this reason, these results are referred to here as path coefficients, temporal ordering effects, predictive effects, or simply effects, rather than "causal" effects.

A potentially important limitation that our study shares with much research is the focus on individual student predictors of aggression and victimization, rather than on broader contextual variables. At the individual student level we demonstrated the robustness of support for our results in relation to gender, year in school, and their interaction as covariates, but did not extend this to consideration of these background variables as moderator variables. We also note that that the focus of our study was on relational aggression and victimization, so that it is important to test the generalizability of the results to other components of aggression and victimization—including gender differences that are likely to be larger, particularly in relation to physical aggression and victimization. On the broader contextual level, Cook et al. (2010, p. 76) note that this focus on individual differences results in what they referred to as a "'personalized' bias, both in terms of its etiology and its consequences" and ignores the fact that childhood aggression and victimization necessarily take place in a broader context (e.g., the school). They go on to note that it is ironic that most studies endorse a whole-school approach, even though there has been limited research into the contextual predictors of bullying, aggression, and victimization. Further, they suggest that interventions need to address both contextual and individual factors.

What are the unique methodological and design contributions of the present investigation in relation to the many hundreds of studies of relations between depression and victimization?

Many of these studies— but certainly not all— have used psychometrically weak measures (or at least do not provide rigorous psychometric tests of their variables); most— but certainly not all— have been based on manifest models and variables that do not control for the inevitable measurement error—particularly the complex structure of measurement error typical in longitudinal panel studies; many are based on a single wave of data, which makes problematic any conclusions about temporal ordering. A few have considered multiple waves of data, but very few have considered as many waves as are considered here, providing strong tests of the invariance of factor loadings and path coefficients over time; most studies have related depression to victimization or, perhaps, to aggression, but few have included depression together with victimization and aggression in the same model in order to evaluate the reciprocal effects of the three constructs in relation to one another. Apparently no previous research has incorporated all these strengths into a single study, but certainly at least some of these strengths are increasingly being incorporated into applied research, as noted in our reviews of the literature presented earlier. In this respect both the strengths of the present investigation as well as potential limitations provide direction for further research.

Conclusion

In conclusion, this substantive-methodological synergy has introduced stronger methodological approaches to evaluating the temporal ordering of childhood depression, victimization, and aggression; reviewed research in relation to this methodology approach; and applied the REM to appropriate data. Victimization and aggression were reciprocally related, each having positive predictive effects on the other. Consistently with the symptoms-driven model, depression had a positive effect on victimization, but victimization did not lead to increased depression beyond what could be explained in terms of prior depression. Although aggression was positively correlated with depression within each wave of data, neither factor had a predictive effect on the other in the REM. In support of the assumption of developmental equilibrium, the results were consistent across the six waves. The results have important implications for policy, practice, and interventions, and provide clear support for the growing literature that suggests that many of the negative interpersonal and emotional problems associated with victimization might, at least in part, reflect characteristics that aggressors use to target vulnerable victims rather than— or in addition to—the negative consequences of being a target of aggression. Taken together, these findings suggest that the design of intervention programs must consider the dynamic nature of aggression and victimization rather than focusing on either one of these constructs in isolation. Rather, it might be more important to identify ways that do not involve retaliation, to help youth respond to aggressive peers. It will also be important to intervene as early as possible when children show symptoms of depression, as this appears to be an important predictor of subsequent victimization. These results, coupled with the reciprocal effects between aggression and victimization, dictate that interventions need to be holistic, addressing aggression, victimization, and whole-school contexts (including teachers, parents, and students who might be neither aggressors nor victims). As emphasized by Cook et al. (2010), it makes little sense to focus on individuals without also changing the context, and vice versa, so that the most promising interventions focus at the levels of the individual student, the peer group, and the broader contexts.

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