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The longitudinal associations between substance use, crime, and social risk among emerging adults: A longitudinal within and between-person latent variables analysis

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ABSTRACT

Background: The reciprocal relationship between crime and substance use is well known. However, when examining this relationship, no study to date has disaggregated between- and within-person effects, which represents a more methodologically sound and developmentally-appropriate analytic approach. Further, few studies have considered the role of social risk (e.g., deviant peers, high-risk living situations) in the aforementioned relationship. We examined these associations in a group of individuals with heightened vulnerability to substance use, crime and social risk: emerging adults (aged 18–25 years) in substance use treatment.
Methods: Participants were 3479 emerging adults who had entered treatment. We used auto-regressive latent growth models with structured residuals (ALT-SR) to examine the within-person cross-lagged association between crime and substance use and whether social risk contributed to this association. A taxonomy of nested models was used to determine the structural form of the data, within-person cross-lagged associations, and between-person associations.
Results: In contrast to the extant literature on cross-lagged relations between crime and substance use, we found little evidence of such relations once between- and within-person relations were plausibly disaggregated. Yet, our results indicated that within-person increases in social risk were predictive of subsequent increases in crime and substance use. Post-hoc analyses revealed a mediation effect of social risk between crime and substance use.
Conclusions: Findings suggest the need to re-think the association between crime and substance use among emerging adults. Individuals that remain connected to high-risk social environments after finishing treatment may represent a group that could use more specialized, tailored treatments.

1. Introduction

It is widely accepted that substance use and crime are strongly correlated (White, 1990; Farrell et al., 1992; White et al., 1999; D'Amico et al., 2008a). Indeed, a growing body of theoretical and empirical work suggests that substance use and crime may affect each other reciprocally, such that each perpetuates or exacerbates the other over time (Mason and Windle, 2002; D'Amico et al., 2008a). However, there are notable methodological shortcomings of the current literature that may affect the conclusions and implications of these studies. In the present manuscript, we address these shortcomings in two ways. First, we address the methodological problems resulting from the way that these reciprocal processes are typically modeled. Second, we address the influence of context on the association between substance use and crime. Despite the well-recognized connection between social risk, such as deviant peer affiliation, with delinquency, crime, and substance use (Fergusson et al., 2002; Van Ryzin and Dishion, 2014), these social contexts have been largely absent from the extant literature when examining the reciprocal relations between substance use and crime. Indeed, social risk may be a critical mechanism through which substance use manifests in crime.

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1.1. Disaggregating within and between person effects

This paper extends work in this area by using recent advances in modeling longitudinal relationships. The most common method for testing reciprocal relationships—auto-regressive, cross-lagged (ARCL) structural equation models—will typically yield estimates that are difficult (if not impossible) to interpret because they do not allow for the disaggregation of between- and within-person effects. For example, D'Amico et al. (2008a) utilized an ARCL model to understand the association between substance use and crime among a high risk adolescent sample. Results indicated a fully cross-lagged relationship between the two constructs, leading researchers and clinicians to draw conclusions for treatment practice and policy. Others have used similar methods to demonstrate comparable relationships between deviant peer association and substance use (see Mason and Windle, 2002 and Van Ryzin et al., 2012). However, these studies have neglected to include within-person effects, which can interfere with proper interpretation of true associations. For instance, typical ARCL specifications yield cross-lagged estimates that are an odd amalgam of between-and within-person estimates, weighted as a function of their respective reliabilities (Berry and Willoughby, 2016). These estimates are difficult to interpret and only plausible given the assumption that the between- and within-person effects are identical—an assumption that is incredibly rare in practice. For example, it is highly unlikely, that changes in substance use from one's 'typical' level (i.e., individual mean) would be identical to changes in substance use compared to other people (i.e., grand mean). The former measures state-like, time-variant deviations in substance use and the latter measures trait-like, time-invariant deviations in substance use, two substantively different levels of analysis with very different meanings and implications. As such, there is good reason to suspect that the extant findings regarding reciprocal relations between substance use and crime require some re-evaluation.

Recent models for longitudinal data, such as the auto-regressive latent growth model with structured residuals (ALT-SR) introduced by Curran et al. (2014), improve prediction because they allow one to simultaneously consider between-person relations among more systematic – or trait-like – aspects of substance use and social risk and crime (e.g., mean levels, growth rates), while modeling reciprocal relations between these variables as they manifest *within*-individuals over time. This provides two advantages. First, it anchors the reciprocal processes at an arguably more developmentally relevant level of analysis – *within*-person. Second, it strengthens the internal validity of the reciprocal effects as each individual serves as his/her own control group and therefore all time-invariant confounds are controlled.

1.2. Social risk and its association with substance use and crime

This paper also extends work in this area by addressing social context. Most studies do not consider social risk (i.e., association with deviant peers and high risk living situations) when investigating the reciprocal associations between substance use and crime. This is a notable limitation in the literature given that social risk is strongly associated with engagement in delinquent behavior (Prinstein et al., 2001; Paternoster et al., 2013; Helms et al., 2014) and substance use (Andrews et al., 2002; Butters, 2004; Henry et al., 2011; Lau-Barraco et al., 2012; Davis et al., 2015). It is possible that social risk may be an important mechanism underlying the relation between substance use and criminal behavior. Further, no studies have investigated these constructs together and in tandem with a clinical (in substance use treatment) emerging adult sample. This is an important endeavor as emerging adults have the highest prevalence of substance use compared to adolescents and adults, and they are also the least likely to complete substance use treatment (Hedden and Gfroerer, 2011; SAMHSA, 2014). Emerging adults exhibit the highest rates of binge drinking (37.9%), cannabis (19%), alcohol (59.6%), and illicit drug use (21.5%) compared to adolescents and older adults (SAMHSA (NSDUH), 2014) and represent 34% of all substance use disorder treatment admissions in the United States (SAMHSA, 2013). Further, individuals involved in the criminal justice system (e.g., engaging in criminal behavior) have approximately a five times higher rate of substance use and three times higher rate of substance use disorders (Aarons et al., 2001; Grisso and Underwood, 2004). Prior research and theory suggests that emerging adulthood is a time of instability and change that includes identity development and autonomy (Arnett, 2005), and peers (especially deviant peers) may play a large role in whether youth become involved in substance use and crime. Therefore, it is important to understand the mechanisms that are most salient in predicting positive treatment outcomes or behaviors for emerging adults following treatment.

Including social risk may help explain the reciprocal relationship between substance use and crime because exposure to high social risk may create a social context that encourages and reinforces increased involvement in substance use and crime. Specifically, associations with deviant peer groups and higher risk living environments (e.g., people you live with) have been found to be significant predictors and mediators of substance use and dependence in adolescent samples (Van Ryzin et al., 2012; Van Ryzin and Dishion, 2014). However, no study to date has disaggregated within and between-person effects, thus allowing for an examination of a *within*-person mediation model. Investigating these relations at the within-person level can shed light on important within-person changes or shifts (e.g. social risk) that affect the relationship with subsequent substance use and crime, something current ARCL models cannot do.

1.3. Summary and hypotheses

The current study moves the field forward by testing three hypotheses regarding the associations between social risk, crime, and substance use over time. First, we hypothesized that the between-person relationship between substance use and crime would exist such that, on average, individuals who reported more substance use would also report more involvement in crime. Similarly, we hypothesized that between-person increases in social risk would be associated with increased crime and substance use. Second, we expected that the within-person cross-lagged relationship between substance use and crime would likely remain yet be attenuated in the context of the more rigorous within-person design. Third, we hypothesized that similar cross-lagged relations would be evident for social risk with substance use and crime, and conjectured an indirect relation, whereby the within-person link between substance use and crime would manifest partially via its lagged relation with social risk.

2. Methods

2.1. Participants

Human subjects approval was received by the Institutional Review Board prior to all analysis. We obtained data on emerging adults aged 18–25 years ($N = 3479$) entering substance use treatment from Chestnut Health Systems through the Global Appraisal of Individual Needs (GAIN) Coordinating Center. Persons entering treatment were referred from a variety of sources such as the juvenile justice system, a probation officer, parents, partners, or self-referral. Treatment sites were spread across the United States and included agencies trained to administer the GAIN and whose records were part of a national data set managed by GAIN Coordinating Center. The treatment received at each site varied greatly and depended on grant funding agencies (e.g., cognitive behavioral therapy, community reinforcement approach). Treatment length also varied, but generally participants remained in treatment between the baseline assessment and three month follow up.

2.2. Measures

2.2.1. Demographics. Gender was coded with female as the reference group. Race/ethnicity was dichotomized with nonwhite as the reference group

2.2.2. Global appraisal of individual needs (GAIN) scales. The GAIN is a valid semi-structured assessment tool that addresses various life domains, including measures on substance use, crime, social risk, mental health, sex risk behaviors, health behaviors, and treatment specific items that are consistent with the *DSM-IV-TR* (American Psychiatric Association, 2000) criteria for substance use disorders and mental health diagnoses. Participants entering treatment completed assessments at baseline, 3, 6, and 12 months. To account for lags in the three month follow-ups, the GAIN utilizes a calendar or personalized anchor system to increase reliability of items referring to past 90 day and past year, which has been shown to be as reliable as time line follow back (Sobell and Sobell, 1992; Dennis et al., 2004).

2.2.2.1. Substance use. The GAIN substance frequency scale (SFS; $\alpha = 0.82$) is the average percent of past 90 day alcohol, heavy alcohol, cannabis, and illicit drug use, and problems associated with substance use. Higher scores on this scale represent a greater frequency of days on which participants experienced substance use and substance-related problems (McLellan et al., 1994).

2.2.2.2. Crime. The GAIN General Crime Scale (GCS; $\alpha = 0.87$) is a count of the number of various types of illegal activities (e.g., three subscales include interpersonal crime, property crime, and drug crime) endorsed in the past 90 days (Rosen, 1995; Dennis et al., 2006; Conrad et al., 2010). Higher scores on the GCS indicate involvement in a greater amount of criminal activity.

2.2.2.3. Social risk. The GAIN Environmental Risk Scale (ERS; $\alpha = 0.68$) assesses social risk. Participants identify individuals with whom they live, work and socialize that are involved in delinquent (e.g., illegal activities, fighting) and protective (e.g., in school or working, in recovery) behaviors. The ERS has three subscales including the Living Risk Scale (e.g. people with whom who the client lives), Vocational Risk Scale (e.g., people with whom client works), and the Social Risk Scale (e.g., people with whom the client socializes). Participants indicated how many of their friends were involved in each activity. Higher scores indicate that the participant is associating with more people who are involved in deviant or illegal activities, who are not in school or working, and who engage in arguing or fighting.

2.3. Analytic approach

To demonstrate the differences between the ARCL and ALT-SR models, we fit an ARCL model analogous to those found in the extant literature, which examined the reciprocal relation between substance use and crime. This ARCL model therefore specified full cross lags between substance use, crime, and social risk. We then fit a more developmentally appropriate ALT-SR model and compared the differences between the two modeling approaches.

To partition the within- and between-person variance, we fit taxonomies of ALT-SR models in the context of structural equation modeling (Curran et al., 2014). This specification allowed us to fit the more 'traditional' ARCL model, while also partitioning variance at the two levels of analysis. The within-person relations are captured by the autoregressive and cross-lagged paths; the between-person components are captured by the latent growth means and (co) variances. In the context of ALT-SR correlating (or regressing) latent intercepts and random slopes will give you the disaggregated between person effect (represented by $\varphi_{\text{standardized}}$), thus pushing within-person variance into the residual cross-lagged portion of the model.

We specified the respective between-person trajectories as piecewise functions. The latent intercept represents the estimated population mean level and (residual) between-person variance of the given variable (i.e., beginning of treatment). The mean of the latent "shift" parameter represents the immediate time-specific shift in the given variable upon entering the "treatment phase" (0–3 months). Finally, we modeled a latent linear slope occurring over the "post-treatment" phase (3–12 months). Preliminary models indicated that this be constrained to be equal between individuals. In each model we controlled for participant age, race, and gender by regressing all control variables on the latent intercept, shift and growth parameter. All (residual) latent co-variances were estimated. When standardized, they represent the between-person partial correlation (after adjusting for age, gender, and race/ethnicity). To determine if the shift or linear growth (after the shift) parameters among our latent substance use, crime and social risk constructs should vary randomly, we tested each separately. After testing for the appropriate functional form only the social risk shift parameter was allowed to vary randomly between individuals.

Our final model is a result of a taxonomy of models in which: Model 1 (M1) established a baseline null cross-lagged model (i.e., auto-regressive paths only); M2 addressed the extant literature–we freed the cross-lagged relations between substance use and crime–with our specifications, however, disaggregating the two levels of inference; and M3 freed the cross-lagged parameters associated with social risk (see Supplementary Figs. 1–3 for details on the model building process). Fit statistics were used to assess improvement in model specification. We used Comparative Fit Index (CFI) of 0.95 or greater, Root Mean Square Error of Approximation (RMSEA) of 0.05 or less, and Standardized Root Mean Square Residual (SRMR) of less than 0.08 to indicate good model fit.

Our data maintained an unbalanced study design. That is, some individuals were missing data due to how much time elapsed between baseline and the end of the study. The majority of our data could be explained by censoring, or individuals who did not have an opportunity to provide data. For example, of those who could have provided data, approximately 16% and 23% of the participants showed a missing-data pattern consistent with attrition between 3 and 6 or 6 and 12 months after the start of treatment. For individuals who were able to provide data, we utilized full-information maximum likelihood estimator (Mplus 7.3; Muthén and Muthén, 1998–2012) treating all observed predictors as single-item latent variables. To adjust for non-normality, all standard errors were bootstrapped (iterations = 10,000). We used Mplus version 7.3 (Muthén and Muthén, 1998–2012).

3. Results

3.1. Participants

See Table 1 for participant characteristics.

Table 1
Baseline characteristics.

	Total (N = 3479) Mean (SD) or n (%)
Demographics	
Age, in years	20.1 (2.26)
Female n (%)	1017 (29.2)
White n (%)	1295 (37.2)
Hispanic n (%)	1163 (33.4)
African American n (%)	554 (15.9)
Other n (%)	467 (13.4)
Employment n (%)	
Full-Time	486 (14.0)
Part-Time	361 (10.4)
Unemployed and looking for work	1298 (37.3)
Unemployed not looking for work	283 (8.1)
Marital Status n (%)	
Single	3094 (88.9)
Married	298 (8.59)
Separated/divorced	76 (2.2)
Education	
College enrollment n (%)	664 (19.1)
Enrolled but not attending class n (%)	105 (3.0)
Days went to school/training	18.5 (25.8)
Last grade completed	11.0 (1.47)
Psychiatric Disorders	
Major Depressive Scale[a]	3.07 (2.92)
Generalized Anxiety n (%)	676 (19.5)
ADHD[b]	5.76 (6.03)
Substance Use Diagnoses	
Days of marijuana use[c]	17.2 (28.4)
Binge drinking[d]	3.92 (10.5)
Days of alcohol use[e]	6.69 (14.0)
Substance frequency scale	12.1 (15.7)
Substance problem scale	2.61 (4.17)
Criminal Justice	
Criminal justice system index[f]	52.3 (47.4)
Days on probation	31.8 (40.6)

[a] Count of the 12 DSM-IV Major Depressive Disorder symptoms. Range 0–9.
[b] Count of the DSM-IV Attention Deficit Hyperactivity Disorder symptoms. Range 0–18.
[c] Days of marijuana use in past 90 days.
[d] Days of drinking 5 or more drinks or to intoxication in the past 90 days.
[e] Days of alcohol consumption in past 90 days.
[f] Percent of criminal justice days.

3.2. Between-person associations (ARCL)

The ARCL model demonstrated good fit (CFI = 0.974, RMSEA = 0.024, SRMR = 0.038), and, similar to previous work in this area, showed full cross-lagged effects between substance use and crime, substance use and social risk, and a lagged effect of social risk to crime. The only non-significant path was from crime to social risk. See Fig. 1 for estimates and standard errors.

3.3. Between-person associations (ALT-SR)

Overall mean trajectories for substance use (B = −5.87, SE = 0.286, p < 0.01), crime (B = −1.42, SE = 0.047, p < 0.01), and social risk (B = −2.06, SE = 0.169, p < 0.01) showed steep declines from baseline to three months (shift-parameter). Growth following the shift parameter slightly increased for substance use (B = 0.067, SE = 0.168, p = 0.69) and social risk (B = 0.080, SE = 0.115, p = 0.49) over the next two follow-ups, with crime (B = −0.056, SE = 0.016, p < 0.01) slightly decreasing through 12-month follow up.

The intercept factors represented by the latent growth model indicated moderate to strong associations for between-person substance use, crime, and social risk at baseline. Between-persons, an individual who engaged in crime also tended to use substances more often ($\varphi_{standardized}$ = 0.513) and was exposed to higher levels of social risk than those who engaged in less crime over this period ($\varphi_{standardized}$ = 0.384). Similarly, those experiencing greater social risk tended to engage in more substance use ($\varphi_{standardized}$ = 0.602).

3.4. Within-Person cross-lagged associations (ALT-SR)

Our first model included estimating auto-regressive paths while constraining all other cross-lag associations to zero (see Supplemental Fig. 1). Doing this allowed our models to remain nested (e.g., co-variance matrix). As shown in Table 2, positive auto-regressive relations were evident across the social risk, substance use, and crime variables, even after accounting for the systematic growth functions. As expected, tests of nested models indicated that the respective magnitudes of these auto-regressive estimates were less pronounced during the treatment phase compared to the post treatment phase (CFI = 0.966, RMSEA = 0.029, SRMR = 0.046).

In Model 2 we estimated cross-lag associations between substance use and crime, while constraining social risk to zero (see Supplemental Fig. 2). All within-time correlations, control variables, and auto-regressive paths were estimated. In contrast to the extant literature and our findings from the ARCL model, there was little evidence of such cross-lagged relations when the between- and within-person relations were plausibly disaggregated. The respective estimates were small and statistically non-significant in both directions (CFI = 0.970, RMSEA = 0.029, SRMR = 0.042).

In our final model, we freed social risk paths, allowing all cross-lag associations to be estimated. As displayed in M3 (Table 2), there was an indication that within-person increases in social risk were predictive of subsequent increases in crime. There was no support for a bi-directional relation—within-person increases in crime were not predictive of within-person increased in social risk. Tests of model constraints indicated that the magnitudes of the respective cross-lagged estimates were statistically identical during the pre- and post-treatment phase (CFI = 0.971, RMSEA = 0.028, SRMR = 0.044) (see Fig. 2 and Supplemental Fig. 3).

As hypothesized, within-person increases in substance use were predictive of increased social risk. Findings were consistent with our hypothesis that the relation between substance use and crime is likely indirect via connections with increased social risk. We tested this explicitly by bootstrapping 95% standard errors (iterations = 10,000) for the product of the estimated parameters comprising this indirect pathway. The pathway was modest in an absolute sense (indirect effect = 0.01, p = 0.04); yet was statistically significant, suggesting that exposure to social risk is likely a mechanism through which substance use may impact crime (see Supplementary Fig. 4).

4. Discussion

The current study advances the literature both methodologically and substantively by examining the longitudinal effects of social risk, crime, and substance use among an emerging adult treatment sample. Similar to previous research, the ARCL model showed cross-lagged effects between substance use and crime. In contrast, when using the more developmentally appropriate ALT-SR model, which accounted for both within- and between-person effects, the association between substance use and crime was no longer significant. In addition, we found that social risk mediated the association between substance use and crime.

From a methodological stance, when using the traditional ARCL model we came to a similar conclusion as previous work (D'Amico et al., 2008a) in that we found a significant cross-lagged association between crime and substance use. However, when we modeled at the within-person level, we did not find a cross-lagged association between substance use and crime, which was contrary to our hypothesis. Our findings were robust even when we did not include social risk in the model, such that reporting more substance use (or crime) at one time point was not indicative of increased crime

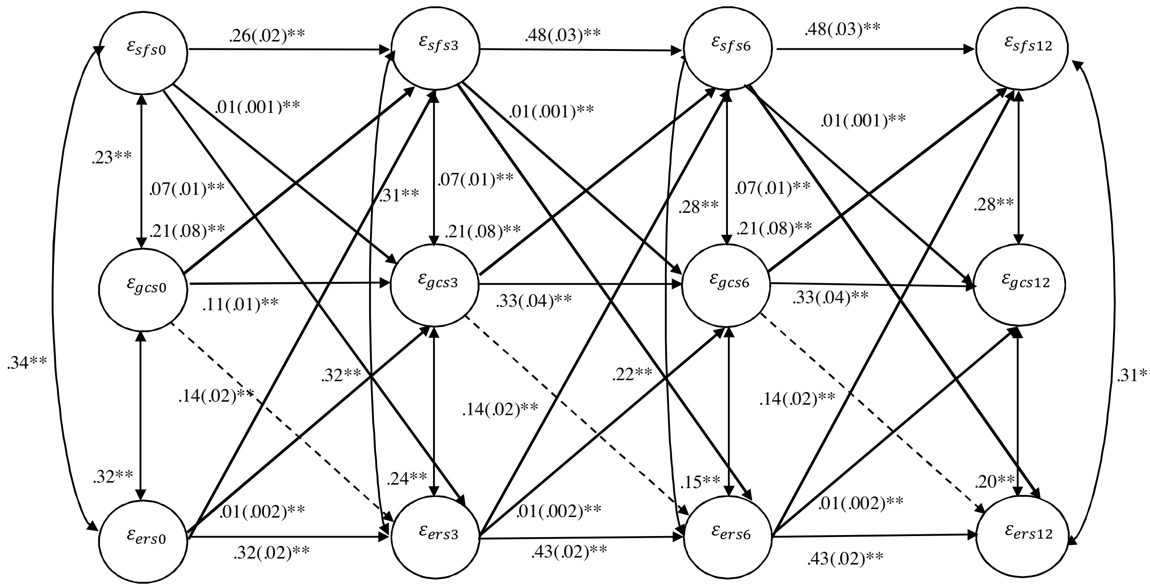

Fig. 1. Traditional ARCL model for between person cross-lagged effects. Parameter estimate (Standard Error).
Note: Bold line indicate significant effect, dashed line represents non-significant path. SFS = Substance use measured by the Substance Frequency Scale, ERS = Social Risk measured by the Environmental Risk Scale, GCS = Crime measured by the General Crime Scale. 0 = Baseline, 3 = 3 month follow up, 6 = 6 month follow up, and 12 = 12 month follow up.
Fit Statistics: CFI = 0.974, RMSEA = 0.024, SRMR = 0.038.

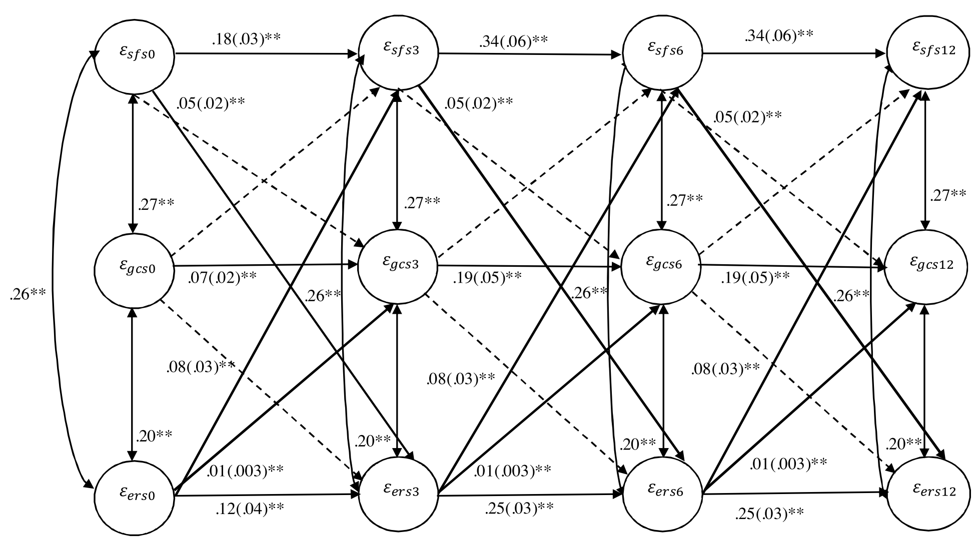

Fig. 2. Final ALT-SR model displaying within-person cross-lagged effects. Parameter estimate (Standard Error).
Note: Bold line indicate significant effect, dashed line represents non-significant path. SFS = Substance use measured by the Substance Frequency Scale, ERS = Social Risk measured by the Environmental Risk Scale, GCS = Crime measured by the General Crime Scale. 0 = Baseline, 3 = 3 month follow up, 6 = 6 month follow up, and 12 = 12 month follow up.

(or substance use) at the adjacent time point. Traditional ARCL models produce estimates that are an amalgam of both between and within-person variance (e.g., convergence). Because the ALT-SR model allows us to estimate effects at both levels, we can interpret findings in a more appropriate (developmentally) and meaningful (statistical) way. For example, though we found that on average (between-persons) increased substance use was associated with increased changes in crime, and vice versa, we did not find significant cross-lagged associations at the within-person level. This is an important distinction as it helps us better understand how well treatment may work at the *individual* level.

Our within person analysis also showed that, on average, individuals who reported higher social risk also reported higher average rates of substance use and crime, and vice versa. It is well known that associating with higher risk environments post treatment can provide the social context for continued risk taking behavior such as substance use and crime (Simpson et al., 2000). However, previous studies have not accounted for social risk or high-risk living situations when examining the association between substance use and crime. This is important to understand because changing substance use or criminal behavior for emerging adults receiving treatment may not be enough to support positive post-treatment behavior. If we had only utilized the traditional ARCL model we would have made conclusions similar to prior research (Mason and Windle, 2002; D'Amico et al., 2008a) such that interventions targeting either substance use or delinquent (crim-

Table 2
Reciprocal relations between substance use, criminal behavior and environmental risk.

	Model 1[a] Parameter (*SE*)	Model 2[b] Parameter (*SE*)	Model 3[c] Parameter (*SE*)
Within-Person Cross-Lags			
$\text{Crime}_t\,\textit{on}\,\text{SubstanceUse}_t$	–	0.004 (0.002)	0.003 (0.002)
$\text{SubstanceUse}_t\,\textit{on}\,\text{Crime}_t$	–	0.183 (0.101)	0.131 (0.105)
$\text{EnvironmentalRisk}_t\,\textit{on}\,\text{Crime}_t$	–	0.024 (0.065)	0.066 (0.069)
$\text{Crime}_t\,\textit{on}\,\text{EnvironmentalRisk}_t$	–	–	0.010 (0.003)*
$\text{EnvironmentalRisk}_t\,\textit{on}\,\text{SubstanceUse}_t$	–	0.043 (0.013)*	0.054 (0.015)*
$\text{SubstanceUse}_t\,\textit{on}\,\text{EnvironmentalRisk}_t$	–	–	0.076 (0.034)*
Auto-Regressive			
$\text{Crime}_{t2}\,\textit{on}\,\text{Crime}_{t1}$	0.073 (0.016)*	0.077 (0.017)*	0.069 (0.017)*
$\text{Crime}_t\,\textit{on}\,\text{Crime}_t$	0.205 (0.048)*	0.208 (0.049)*	0.190 (0.050)*
$\text{SubstanceUse}_{t2}\,\textit{on}\,\text{SubstanceUse}_{t1}$	0.160 (0.024)*	0.187 (0.033)*	0.181 (0.033)*
$\text{SubstanceUse}_t\,\textit{on}\,\text{SubstanceUse}_t$	0.308 (0.059)*	0.349 (0.067)*	0.341 (0.066)*
$\text{EnvironmentalRisk}_{t2}\,\textit{on}\,\text{EnvironmentalRisk}_{t1}$	0.149 (0.030)*	0.129 (0.032)*	0.148 (0.034)*
$\text{EnvironmentalRisk}_t\,\textit{on}\,\text{EnvironmentalRisk}_t$	0.196 (0.030)*	0.168 (0.031)*	0.195 (0.031)*
(Co) Variances			
$\text{SubstanceUse}_{int}\,\textit{with}\,\text{Crime}_{int}$	2.12 (0.290)*	1.58 (0.464)*	1.50 (0.457)*
$\text{SubstanceUse}_{int}\,\textit{with}\,\text{EnvironmentalRisk}_{int}$	20.91 (1.50)*	17.86 (2.19)*	14.8 (3.01)*
$\text{EnvrionmentalRisk}_{int}\,\textit{with}\,\text{Crime}_{int}$	1.34 (0.156)*	1.21 (0.185)*	.884 (0.222)*
$\text{SubstanceUse}_{int}$	6.44 (2.37)*	6.36 (2.36)*	6.33 (2.37)*
Crime_{int}	3.65 (0.447)*	3.66 (0.449)*	3.66 (0.450)*
$\text{Environmental Risk}_{\text{int}}$	35.7 (1.42)*	35.7 (1.42)*	35.7 (1.38)*
$\text{SubstanceUse}_{it0}$	38.8 (6.06)*	32.5 (8.41)*	31.5 (8.64)*
Crime_{it0}	0.296 (0.069)*	0.275 (0.075)*	0.278 (0.073)*
$\text{EnvironmentalRisk}_{it0}$	18.7 (1.74)*	18.6 (1.74)*	17.1 (2.04)*
Residual (Co) Variances			
$\text{SubstanceUse}_{it1-it4}$	97.3 (5.81)*	100.4 (6.44)*	100.6 (6.34)*
$\text{Crime}_{it1-it4}$	1.03 (0.082)*	1.04 (0.084)*	1.03 (0.084)*
$\text{EnvironmentalRisk}_{it1-it4}$	44.49 (1.97)*	43.97 (1.93)*	45.1 (1.90)*
Fit Statistics			
−2LL	−98408.22	−98396.63	−98388.86
χ^2	292.63	2689.47	253.916
df	74	70	68
RMSEA[d]	0.029	0.029	0.028
SRMR[e]	0.043	0.042	0.041
CFI[f]	0.967	0.970	0.972

Note: Estimates for age, gender, and race regressed on all latent intercept, shift, and linear growth parameters are not shown for readability.
In the table above, subscripts identify time of measurement. For example, a single t indicates paths were constrained to be equal over time. Subscripts such as t_1, t_2, t_3 indicate paths were estimated at the respective time point. Subscript *int* indicates latent intercept (mean level) to obtain between-person parameter estimates. Subscripts with an epsilon (*it*) indicate residual variance measured from Time 1 to Time 4.
df = ° of freedom. RMSEA = Root Mean Square Error; CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residual.
[a] Model 1 includes estimates for autoregressive paths only.
[b] Model 2 includes substance use, criminal behavior, with environmental risk constrained to zero.
[c] Model 3 includes all estimated cross-lag paths.
[d] RMSEA indices below 0.05 are considered to be representative of good model fit.
[e] SRMR indices below 0.05 are considered to be representative of good model fit.
[f] CFI scores above 0.95 are indicative of good model fit.
* $p < 0.05$.

inal) behavior may result in a reduction in one or both behaviors. However, our results instead emphasize the importance of social risk on post-treatment behavior. Specifically, we found that emerging adults who reported more substance use at one time point demonstrated increased social risk at the next time point, which was subsequently associated with increased crime. Findings support a small literature that argues there is little evidence to support a causal link between substance use and crime and these associations are weak, at best (Huizinga et al., 1989; Dembo et al., 1995, 2002).

Furthermore, although prior research has shown deviant peer association can mediate the relationship between subsequent substance use and dependency (Van Ryzin et al., 2012; Van Ryzin and Dishion, 2014), these studies use a between-person modeling approach that does not partition variance at multiple levels of analysis. Our model is an improvement on prior analyses as it controls for all between-person measures and unobserved confounds, and specifically examines how deviations from one's 'typical' level of substance use (i.e., individual mean) can affect changes in social risk at subsequent time points, and, further, how social risk can effect changes in crime. Future research should include disaggregation (e.g., within- and between-person) when evaluating effects of crime and substance use over time and, if possible, infuse effects of high risk environments (e.g., deviant peers, low parental warmth (high hostility), and neighborhood disorganization).

Viewing social risk and high risk living situations as a mechanism of change between substance use and crime may help practitioners who work with individuals reporting both criminal activity and high substance use. That is, emerging adults who remain connected to their high risk social networks post-treatment may be at higher risk of both continued substance use and criminal behavior. Interventions that focus on changing one's environment, such as the Community Reinforcement Approach (Meyers et al., 1998) may aid in reducing both substance use and crime (Meyers et al., 2011). Other approaches, such as motivational interviewing, have shown to lead to reductions in peer aggression, victimization, delinquency and substance use (Jensen et al., 2010; Cunningham et al., 2012). Thus, during the treatment phase, practitioners could perhaps identify those emerging adults who may have stronger connections to risky peer or high-risk living environment and provide them with booster sessions. For example, providing brief motivational interviewing through either face-to-face or electronic (e.g., computer, text) intervention has been shown to reduce the amount of time that youth spend interacting with deviant peers (D'Amico et al., 2008b), and also reduces peer aggression and violence, thus potentially also reducing substance use and crime rates (Feldstein and Ginsburg, 2006; McMurran, 2009; Cunningham et al., 2012). However, most interventions that address deviant peer affiliation are designed for adolescents. Thus, more developmentally appropriate interventions and after care models are warranted for emerging adults.

One limitation of our study is the possibility that our results, derived from a treatment sample of emerging adults, may not be generalizable to non-treatment samples. Also, while ALT-SR provides a more rigorous testing of hypotheses than previous ARLG models, our within person effects represent the fixed, or pooled, effects across individuals over time. Further, all our measures were self-reported, which increases the risk for biased responding (Chan, 2009). Future research could use official arrest records, multiple reporters of environment and urine-analysis to corroborate self-report.

Overall, findings from this study suggest the need to re-think the association between crime and substance use among emerging young adults in treatment. Emerging adulthood is a critical period of development in which one's social environment is constantly changing (Arnett, 2000; Bradley and Wildman, 2002). Individuals that remain connected to high risk environments after finishing treatment may represent a group that could benefit from more specialize, tailored treatments.

Conflict of interest

All authors declare that they have no conflicts of interest.

Contributors

All authors contributed to the design of the study. *Study concept and design*: Merrin, Davis, Berry. Authors (Merrin, Davis, Berry) were responsible for statistical analyses. Authors (Merrin and Davis) wrote the first draft of the manuscript. All authors contributed to and have approved the final manuscript.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.drugalcdep.2016.05.009.

References

Aarons, G.A., Brown, S.A., Hough, R.L., Garland, A.F., Wood, P.A., 2001. Prevalence of adolescent substance use disorders across five sectors of care. J. Am. Acad. Child Adolesc. Psychiatry 40, 419–426.

American Psychiatric Association, 2000. Diagnostic and Statistical Manual of Mental Disorders: DSM-IV-TR®. American Psychiatric Association, Washington D.C.

Andrews, J.A., Tildesley, E., Hops, H., Li, F., 2002. The influence of peers on young adult substance use. Health Psychol. 21, 349–357.

Arnett, J.J., 2000. Emerging adulthood: a theory of development from the late teens through the twenties. Am. Psychol. 55, 469–480.

Arnett, J.J., 2005. The developmental context of substance use in emerging adulthood. J. Drug Issues 35, 235–254.

Berry, D., Willoughby, M., 2016. On the practical interpretabilty of cross-lagged panel models: once more unto the breach, dear friends? Child Dev. ()in press.

Bradley, G., Wildman, K., 2002. Psychosocial predictors of emerging adults' risk and reckless behaviors. J. Youth Adolesc. 31, 253–265.

Butters, J.E., 2004. The impact of peers and social disapproval on high-risk cannabis use: gender differences and implications for drug education. Drugs Educ. Prev. Policy 11, 381–390.

Chan, D., 2009. So why ask me? Are self-report data really that bad. In: Lance, C., Vandenberg, R.J. (Eds.), Statistical and Methodological Myths and Urban Legends: Doctrine, Verity and Fable in the Organizational and Social Sciences. Routledge/Taylor & Francis Group, New York, NY, pp. 309–336.

Conrad, K.J., Riley, B.B., Conrad, K.M., Chan, Y., Dennis, M.L., 2010. Validation of the crime and violence scale (CVS) against the Rasch measurement model including differences by gender race, and age. Eval. Rev. 34, 83–115.

Cunningham, R.M., Chermack, S.T., Zimmerman, M.A., Shope, J.T., Bingham, C.R., Blow, F.C., Walton, M.A., 2012. Brief motivational interviewing intervention for peer violence and alcohol use in teens: one-year follow-up. Pediatrics 129, 1083–1090.

Curran, P.J., Howard, A.L., Bainter, S.A., Lane, S.T., McGinley, J.S., 2014. The separation of between-person and within-person components of individual change over time: a latent curve model with structured residuals. J. Consult. Clin. Psychol. 82, 879.

D'Amico, E.J., Edelen, M.O., Miles, J.N., Morral, A.R., 2008a. The longitudinal association between substance use and delinquency among high-risk youth. Drug Alcohol Depend. 93, 85–92.

D'Amico, E.J., Miles, J.N., Stern, S.A., Meredith, L.S., 2008b. Brief motivational interviewing for teens at risk of substance use consequences: a randomized pilot study in a primary care clinic. J. Subst. Abuse Treat. 35, 53–61.

Davis, J.P., Merrin, G.J., Berry, D.J., Dumas, T.M., Hong, J.S., Smith, D.C., 2015. Examining within-person and between-person effects of victimization and social risk on cannabis use among emerging adults in substance-use treatment. Psychol. Addict. Behav. 30, 52–63.

Dembo, R., Williams, L., Schmeidler, J., Berry, E., Wothke, W., Getreu, A., Wish, E.D., Christensen, C., 1995. Delinquency and drug use among high risk youths over time. In: Taylor, R.L. (Ed.), African-American Youth: Their Social and Economic Status in the United States. Praeger, New York, pp. 247–279.

Dembo, R., Wothke, W., Seeberger, W., Shemwell, M., Pacheco, K., Rollie, M., Schmeidler, J., Livingston, S., Hartsfield, A., 2002. Testing a longitudinal model of the relationships among high risk youths' drug sales, drug use and participation in index crimes. J. Child Adolesc. Subst. Abuse 11, 37–61.

Dennis, M.L., Funk, R., Godley, S.H., Godley, M.D., Waldron, H., 2004. Cross-validation of the alcohol and cannabis use measures in the Global Appraisal of Individual Needs (GAIN) and Timeline Followback (TLFB; Form 90) among adolescents in substance abuse treatment. Addiction 99, 120–128.

Dennis, M.L., Chan, Y., Funk, R.R., 2006. Development and validation of the GAIN Short Screener (GSS) for internalizing: externalizing and substance use disorders and crime/violence problems among adolescents and adults. Am. J. Addict. 15, s80–s91.

Farrell, A.D., Danish, S.J., Howard, C.W., 1992. Relationship between drug use and other problem behaviors in urban adolescents. J. Consult. Clin. Psychol. 60, 705.

Feldstein, S.W., Ginsburg, J.I., 2006. Motivational interviewing with dually diagnosed adolescents in juvenile justice settings. Brief Treat. Crisis Interv. 6, 218–233.

Fergusson, D.M., Swain-Campbell, N.R., Horwood, L.J., 2002. Deviant peer affiliations, crime and substance use: a fixed effects regression analysis. J. Abnorm. Child Psychol. 30, 419–430.

Grisso, T., Underwood, L.A., 2004. Screening and Assessing Mental Health and Substance Use Disorders Among Youth in the Juvenile Justice System A Resource Guide for Practitioners. US Department of Justice, Washington, DC.

Hedden, S.L., Gfroerer, J.C., 2011. Correlates of perceiving a need for treatment among adults with substance use disorder: results from a national survey. Addict. Behav. 36, 1213–1222.

Helms, S.W., Choukas-Bradley, S., Widman, L., Giletta, M., Cohen, G.L., Prinstein, M.J., 2014. Adolescents misperceive and are influenced by high-status peers' health risk deviant, and adaptive behavior. Dev. Psychol. 50, 2697–2714.

Henry, D.B., Kobus, K., Schoeny, M.E., 2011. Accuracy and bias in adolescents' perceptions of friends' substance use. Psychol. Addict. Behav. 25, 80–89.

Huizinga, D.H., Menard, S., Elliott, D.S., 1989. Delinquency and drug use: temporal and developmental patterns. Justice Q. 6, 419–455.

Jensen, C.D., Cushing, C.C., Aylward, B.S., Craig, J.T., Steele, R.G., 2010. Effectiveness of Motivational Interviewing Interventions for Pediatric Health Behavior Change: A Meta-Analytic Review. Springer, New York, NY, USA.

Lau-Barraco, C., Braitman, A.L., Leonard, K.E., Padilla, M., 2012. Drinking buddies and their prospective influence on alcohol outcomes: alcohol expectancies as a mediator. Psychol. Addict. Behav. 26, 747–758.

Mason, W.A., Windle, M., 2002. Reciprocal relations between adolescent substance use and delinquency: a longitudinal latent variable analysis. J. Abnorm. Psychol. 111, 63.

McLellan, A.T., Alterman, A.I., Metzger, D.S., Grissom, G.R., Woody, G.E., Luborsky, L., O'Brien, C.P., 1994. Similarity of outcome predictors across opiate, cocaine, and alcohol treatments: role of treatment services. J. Consult. Clin. Psychol. 62, 1141.

McMurran, M., 2009. Motivational interviewing with offenders: a systematic review. Leg. Criminol. Psychol. 14, 83–100.

Meyers, R.J., Miller, W.R., Hill, D.E., Tonigan, J.S., 1998. Community reinforcement and family training (CRAFT): engaging unmotivated drug users in treatment. J. Subst. Abuse 10, 291–308.

Meyers, R.J., Roozen, H.G., Smith, J.E., 2011. The community reinforcement approach: an update of the evidence. Alcohol Res. Health 33, 380–388.

Muthén, B., Muthén, L., 1998-2012. Mplus User's Guide: Seventh Edition., Los Angeles, CA.
Paternoster, R., McGloin, J., Nguyen, H., Thomas, K., 2013. The causal impact of exposure to deviant peers: an experimental investigation. J. Res. Crime Delinq. 50, 476–503.
Prinstein, M.J., Boergers, J., Spirito, A., 2001. Adolescents' and their friends' health-risk behavior: factors that alter or add to peer influence. J. Pediatr. Psychol. 26, 287–298.
Rosen, L., 1995. The creation of the uniform crime report: the role of social science. Soc. Sci. Hist. 19, 215–238.
SAMHSA (NSDUH), 2014. Mental Health Services Administration Results from the 2012 National Survey on Drug Use and Health: Summary of National Findings. Substance Abuse and Mental Health Services Administration, Rockville, MD.
SAMHSA, 2013. Treatment Episode Data Set (TEDS): 2001–2011. National Admissions to Substance Abuse Treatment Services. Substance Abuse and Mental Health Services Administration, Rockville, MD.
SAMHSA, 2014. Treatment Episode Data Set (TEDS): 2002–2012. National Admissions to Substance Abuse Treatment Services. Substance Abuse and Mental Health Services Administration, Rockville, MD.
Simpson, D.D., Joe, G.W., Greener, J.M., Rowan-Szal, G.A., 2000. Modeling year 1 outcomes with treatment process and post-treatment social influences. Subst. Use Misuse 35, 1911–1930.
Sobell, L.C., Sobell, M.B., 1992. Timeline follow-back. In: Litten, R., Allen, J. (Eds.), Measuring Alcohol Consumption. Springer, New York, NY, pp. 41–72.
Van Ryzin, M.J., Dishion, T.J., 2014. Adolescent deviant peer clustering as an amplifying mechanism underlying the progression from early substance use to late adolescent dependence. J. Child Psychol. Psychiatry 55, 1153–1161.
Van Ryzin, M.J., Fosco, G.M., Dishion, T.J., 2012. Family and peer predictors of substance use from early adolescence to early adulthood: an 11-year prospective analysis. Addict. Behav. 37, 1314–1324.
White, H.R., 1990. The drug use-delinquency connection in adolescence. In: Weisheit, R.A. (Ed.), Drugs, Crime and the Criminal Justice System. Academy of Criminal Justice Sciences Monograph Series Anderson Publishing Co., Cincinnati, OH, pp. 215–256.
White, H.R., Loeber, R., Stouthamer-Loeber, M., Farrington, D., 1999. Developmental associations between substance use and violence. Dev. Psychopathol. 11, 785–803.