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Continuous Time Modeling with Criminological Panel Data: An Application to the Longitudinal Association between Victimization and Offending

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Abstract

Background: Criminological research shows that there is nearly always a strong and positive association between delinquency and being a victim of crime. This so-called victim-offender overlap is one of the most consistent and best documented findings in criminology. However, examinations using longitudinal panel data are rather scarce. Previous analyses based on latent growth and cross-lagged panel models showed that the developments of victimization and offending are parallel processes that expose similar stability and mutual influence over the period of adolescence and early adulthood (Erdmann & Reinecke, 2018).

Objectives: The present study examines the relationship between victimization and offending over the phase of adolescence and emerging adulthood. The focus is on the application of continuous time dynamic modeling and on comparing results using data from the criminological panel study *Crime in the Modern City*. For the present analyses, seven consecutive panel waves are used that contain information about German adolescents from the age of 14 to 20 years.

Approach: The relationship between victimization and offending is analyzed by continuous time structural equation modeling using the R package `ctsem` (Driver & Voelkle, 2018, 2021). In addition to the unconditional models, relevant predictors (gender, routine activities) are considered in the conditional models. Methododological and substantive aspects of continuous time dynamic modeling are highlighted in the discussion of the results.

Keywords: continuous time modeling, panel analysis, R, ctsem, juvenile delinquency, longitudinal data

Various dynamic specifications of longitudinal models based on structural equations are recently discussed in the methodological literature (Asparouhov & Muthén, 2020; Zyphur et al., 2019a, 2019b; Hamaker et al., 2018; Usami et al., 2019; Montfort et al., 2018). One direction of the discussion is based on potentially misleading findings and interpretations of the classical *cross-lagged panel model* (CLPM, cf. Kessler & Greenberg, 1981; McArdle & Nesselroade, 2014; Rogosa 1979, 1980) regarding the presence, predominance and sign of causal influences. As pointed out by Hamaker et al. (2015), the main critical point of the CLPM is the failure to separate the within-person and the between-person level in the presence of time-invariant trait differences (see also Usami et al., 2019). These arguments are driven by the multilevel structure of the data in panel designs with repeated measurements of the same persons under study. To cope with these major critiques, it has been proposed by Hamaker to extend the CLPM by random intercepts referring to stable between-persons trait differences in the measurements (*random intercept cross-lagged panel model*, RI-CLPM).

The second direction of the discussion is due to the underlying assumption of discrete time points in all major panel models including the CLPM. For example, Voelkle et al. (2012) argue that parameter estimates of the CLPM depend on the length of the time interval between measurement occasions and that this information is not considered in the estimation of the parameters. The authors recommend to model autoregressive processes with stochastic differential equation models using a continuous time approach (*continuous time structural equation model*, CTSEM), which estimate and visualize the continuous time parameters. They also show the derivation of discrete time parameters from these models for specific time intervals of interest. Further explanations and discussions are given in Oud et al. (2018) and Ryan et al. (2018).

This paper intends to provide an application of the CTSEM and to compare model restrictions and model results based on data from a criminological panel study which focuses on the development of delinquency from adolescence to early adulthood. The dynamic relationship between victimization and offending over a certain age period (14 to 20 years) will be the substantive focus of the present analyses. They are based on previous results from cross-lagged panel and growth curve models as well as mixture models considering unobserved heterogeneity in the development of offending and victimization (Erdmann & Reinecke, 2018, 2021).

Erdmann & Reinecke (2018) explored developmental processes of victimization and offending using data from the criminological panel study *Crime in the Modern City* (CrimoC) and found evidence that both processes peak at the age of 14 with a subsequent decrease over the phase of adolescence. Both victimiza-

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tion and offending are highly parallel and positively related processes throughout the juvenile life course. Using the CLPM, positive effects from victimization on offending as well as from offending to victimization could be detected. In addition, the results show a tendency that at a younger age, victimization rather predicts later offending because the highest cross-lagged effects are detected between 14 and 16 years of age (Erdmann & Reinecke, 2018: 336).

Upon these findings, Erdmann & Reinecke (2021) explored interindividual differences in the development of victimization and offending and, accordingly, distinct patterns of trajectories are detected via specification of growth mixture models (e.g., Muthén, 2004). Three groups of offender development (high-level offenders, adolescence-limited offenders, and nonoffenders) and two groups of victimization development (nonvictims and decreasing victims) were identified. Examining the intersection between these trajectories provided more profound insights into the overlap between victimization and offending. The association between the particular group memberships showed that juveniles who exhibit a high level of delinquency over the phase of adolescence are usually in a trajectory of elevated victimization.

The present analyses will consider these previous findings and attempt to overcome restrictions regarding the longitudinal analyses with discrete time points. It has been shown in the literature (e.g., Voelkle et al. 2012) that estimates of autoregressive and cross-lagged parameters of the CLPM are highly dependent on the length of the time interval between the measurements. Under a continuous time framework, like the CTSEM, these dependencies will vanish. Furthermore, discrete time parameters for any time interval can be calculated from the continuous time estimates.

First, we will briefly discuss the continuous time approach as well as the implementation of the continuous time structural equation model in R. After a brief introduction of the panel data and the measurements, the results of the continuous time models will be discussed. Finally, a detailed discussion about advantages and disadvantages of longitudinal modeling in continuous time are provided.

Continuous Time Structural Equation Modeling

In contrast to most panel models, including the CLPM or the RI-CLPM, time is treated as a continuous variable in continuous time modeling. This allows a clear distinction between the oftentimes continuous nature of the constructs under consideration (e.g., vicitimization and offending) and the always discrete occasions at which the measurements take place (e.g., seven panel waves). Practically speaking, treating time as a continuous variable makes the approach independent of the assumption of equidistantly spaced measurement occasions, permits the comparison of parameter estimates across studies with different time intervals, and allows researchers a detailed study of temporal dynamics. A comprehensive introduction to continuous time modeling is beyond the scope of this article, but is provided, for example, by Voelkle et al. (2012). For a recent overview of continuous time models in the social and behavioral sciences, see van Montfort et al. (2018).

Mathematically, the basic idea of continuous time modeling is to predict change over an infinitesimally small time interval, more precisely, to predict the derivative of a vector of variables of interest η(t) with respect to time t (i.e., $\frac{d\eta(t)}{dt}$ by η(t) and possibly other variables. This is formalized in the stochastic differential Equation 1:

$$d\eta(t) = \left(A\eta(t) + b + M\chi(t)\right)dt + GdW(t) \tag{1}$$

Matrix A represents the so-called drift matrix, with auto-effects on the diagonal and cross-effects on the off-diagonals, characterising the temporal relationships of the processes. Vector b denotes the intercepts. Matrix M represents the effects of time dependent predictors χ(t) on the processes η(t). W(t) denotes the so-called Wiener process, a random-walk in continuous time.

Lower triangular matrix G represents the effect of the stochastic error term on the change in η(t), with $Q = GG'$ being the variance-covariance matrix of the diffusion process.

Vector η(t) can be directly observed or latent with the following measurement model equation:

$$y(t) = \tau + \Lambda\eta(t) + \epsilon(t) \tag{2}$$

In Equation 2, the vector y(t) represents the manifest variables, τ represents the vector of manifest intercepts, the matrix Λ contains the factor loadings, and ε is the vector of residuals with error covariance matrix Θ.

To connect the continuous time Equation 1 to the discrete time measurement occasions, the equation is solved for an initial time point and the observed (i.e., discrete) time intervals between measurement occasions in a given study. This is illustrated in Equation 3, where the stars (∗) denote that the discrete time parameters are constrained to the solution of the differential Equation 1. Importantly, because Equation 1 is a comparatively simple linear differential equation, an analytical solution exists and the constraints are well-known (e.g., Oud & Jansen, 2000). For this reason we refrain from reiterating them here, but limit ourselves to referencing the existing literature and the R-package `ctsem` (Driver et al., 2017; Driver & Voelkle, 2018, 2021) that implements these constraints and that will be used later on for the empirical analyses:

$$\eta_u = A^*_{\Delta t_u}\eta_{u-1} + b^*_{\Delta t_u} + M\mathrm{x}_u + \zeta^*_u \tag{3}$$

Note that in contrast to Equation 1, we introduce u as a new symbol in Equation 1 to denote the discrete time measurement occasion u, with U being the set of all measurement occasions. Thus, Δt_u denotes the continuous time interval between two discrete measurement occasions η_u and $\eta_u = -1$.

As described in detail by Driver & Voelkle (2018), parameters in Equation 1 and Equation 3 can differ across individuals. These differences may be explained by time-invariant predictors. In the following, we use the symbol β to denote the vector of effects of time-invariant predictors z.

Continuous time models that can be formulated in terms of Equation 1, 2 and 3 can be conveniently specified and estimated by the R-package `ctsem` (Driver et al., 2017; Driver & Voelkle, 2018, 2021). The initial version of the R package `ctsem` interfaces to OpenMx (Neale et al., 2016) to estimate CTSEM for wide-format panel and time series data based on a full information maximum-likelihood approach. This initial version is now implemented in the R package `ctsemOMX` (Driver et al., 2017). Current versions of the R package `ctsem` provide estimation options for maximum likelihood and Bayesian models, interfacing to Stan (Carpenter et al., 2017). For the latter, panel and time series data has to be provided in long-format.

Data Basis and Measurements

Data

The data used for this methodological examination stem from the research project *Crime in the Modern City* (CrimoC, e.g., Boers et al., 2010; Seddig & Reinecke, 2017; Boers & Reinecke, 2019).[1] The project is funded by the German Research Foundation (DFG) and aims at explaining and monitoring the emergence, development, and desistance of delinquent behaviour throughout adolescence and emerging adulthood. For this purpose, both cross-sectional and longitudinal data on deviant and criminal behaviour as well as on individual characteristics (e.g., values, family characteristics, activities with friends) were collected. The overall project started in the year 2000 with interviews among several cohorts of students in the German cities Münster (started 2000), Bocholt (started 2001) and Duisburg (started 2002). Yet, only the youngest cohort of 7th-graders (13 years old on average in 2002) in Duisburg was followed up to form a long-term panel data set. In 2019, the 13th and last wave of the project was conducted.

The data collection process was initially realized as self-administered paper-and-pencil interviews in school during class supervised by trained interviewers. As

1 Detailed information on the conceptual framework and the design of the study can be obtained from www.crimoc.org.

the students became older and successively started leaving school, their address information were retrieved and the interview mode was gradually changed to postal mode and an optional, subsequent face-to-face mode (for a comprehensive overview, see for example Bentrup, 2007, 2009). The first eight waves of the study (2002 to 2009, age 13 to 20) were conducted annually. When the data collection process was changed to postal mode, the efforts and field time increased accordingly. As a consequence, data were collected biennially after 2009 (five waves from 2011 to 2019, age 22 to 30).

The main objective of the CrimoC-study is to examine the development of delinquent behaviour over the life-course, thus, the according data were retrieved at every wave. Information on victimization, however, were not obtained beyond the panel wave in 2009. Also, the first wave from 2002 cannot be included in analyses that target victimization, because data on victimization experience was only retrieved for certain school types and not for the entire student sample at that time point. Consequently, the panel waves for studying the dynamic relationship between victimization and offending are restricted to the age period from 14 to 20 years. From a criminological point of view, this section of the life-course is well suited for analyzing the association between victimization and offending, because it covers the phase where onset, peak, and emerging desistance of delinquency are most prominent among German juveniles (for details, see Erdmann & Reinecke, 2021).

In summary, the data set employed in the following analyses contains seven waves of data collected annually between 2003 and 2009 (see Figure 1). Respondents who participated at least five out of seven times are included in the analysis (n = 2679) to reduce bias compared to the same panel data set which restricts respondents to those who participated in all seven panel waves (n = 1488).[2]

2 Because of the German data protection law, registered postal adresses could not be used to link the data of the particular panel waves. Instead, individual codes derived from time-stable characteristics (e.g., first letter of prename, day of birth, first letter of mother's prename) were retrieved in each panel wave and used to match the panel data. It has been shown that a sufficient replication of the personal code (i.e., errors in replicating the code were allowed) is associated with gender, delinquency rates, and education. If the analysis would be restricted to those respondents with complete data over all seven panel waves (i.e., continuous participation and sufficient replication of the code), females, respondents with low delinquency/victimization rates, and people with higher education would be overrepresented. Allowing missing participations reduces this bias. Even respondents that did not participate (or who failed to replicate their individual code sufficiently) in two subsequent waves are considered in the seven wave panel data under study.

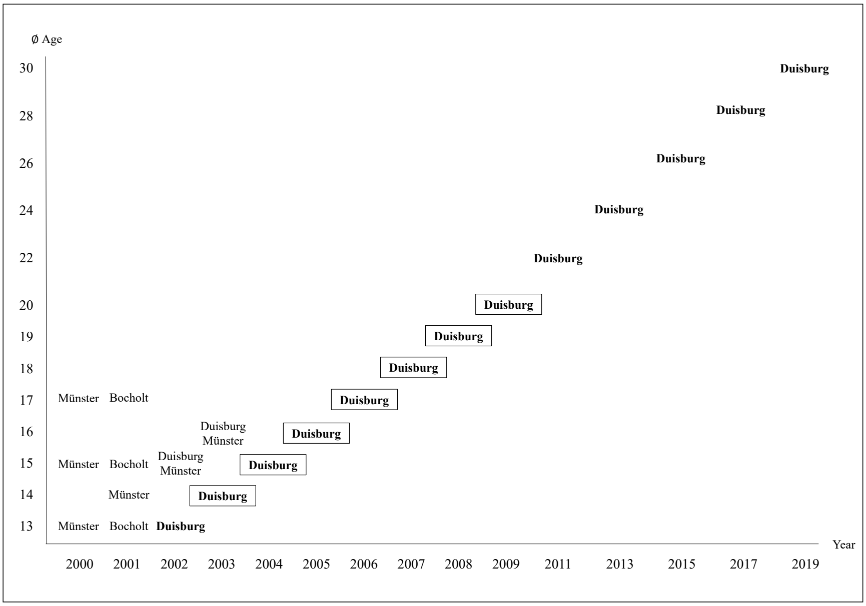

Figure 1 Design of the CrimoC-Study

Measurements

For the CTSEM, measurements of violent victimization and general offending are used as time dependent variables. Also, criminologically relevant predictors of victimization and offending – such as gender and activities with peers – are included in the later conditional models.

Violent Victimization. The present analysis considers violent victimization, which is measured via three violent offenses: *robbery (with threat of violence*), *assault with a weapon*, and *assault without a weapon*. For each offense, participants were asked whether they have experienced this type of victimization within the last year preceding the interview. If yes, they were additionally asked how often they experienced this particular type of victimization. These annual incidences were summed over the three offenses for each wave (i.e., at every age under study)[3]. Hence, the variable reflects the intensity of violent victimization at a certain age. To be in line with previous longitudinal examinations of victimization (e.g., Higgins, Jennings, Tewksbury, & Gibson, 2009; Peterson, Taylor, & Esbensen, 2004;

3 Missing values were allowed for single items. If an item had a missing value, it was treated as zero in the sum. If all three items had missing values, the sum was also coded as missing.

Schreck, Stewart, & Fisher, 2006), the incidence was capped at the value of 12 and all values beyond were aggregated into one category. Thus, the highest category reflects at least 12 victimizations within a year which means at least once a month on average.

General Offending. The measurement of offending consists of 15 offenses covering a broad range of delinquent behaviour. It includes violence *robbery including threat of violence*, *violent bag snatching*, *assault with a weapon*, *assault without a weapon*), property offenses (*shoplifting*, *burglary*, *theft of bicycles*, *theft of cars*, *theft out of cars*, *theft out of a vending machine*, *fencing*, *other theft*), and criminal damage offenses (*graffiti*, *scratching*, *property damage*). The construction of the offending measurement was conducted equivalent to victimization: The annual incidences of the single offenses were added allowing missing values and all values of 12 and higher were combined into one category. Accordingly, the measurement reflects the intensity of offending at the considered time points, that is, at a certain age.

Gender. Gender is one of the most prominent predictors of offending and victimization. Independent of the panel waves (i.e., independent of age), it is expected that males have consistently higher incidence rates of offending and victimization compared to females. Hence, it is included as a time-invariant measurement in the CTSEM to explore possible gender effects. The measurement is binary and contains the two categories male and female.[4]

Routine Activities. The measurements describing the activities are derived from the lifestyle-routine activity approach, which is a combined framework based on routine activity theory (Cohen & Felson, 1979) and lifestyle-exposure theory (Garofalo, 1987; Hindelang et al., 1978). This approach is one of the most prominent theoretical concepts for investigating the association between victimization and offending and has been considered in numerous studies (e.g., Cho & Lee, 2018; Engström, 2018; Mustaine & Tewksbury, 2000; Plass & Carmody, 2005; Pyrooz, Moule, & Decker, 2014; Schreck, Stewart, & Osgood, 2008).

In general, the theory assumes that daily activities regulate the risk of committing criminal acts or – when transferred to victimization - the risk of becoming a victim of crime. A key element, that was later introduced by Osgood et al. (1996), is the distinction between *structured* and *unstructured activities*, also called structured or unstructured socializing. This differentiation states that participation in activities that take place an organized, monitored setting decreases the chances of deviance compared to unstructured and unsupervised activities. Among juveniles, particularly unstructured activities with peers are considered risk factors for crime because delinquent acts are perceived more easier and rewarding when friends are present and authority figures are absent.

4 The questionnaire does not differentiate between sex and gender. Thus, the information on sex provided by the respondents is designated as gender.

Similar mechanisms apply to victimization risk. On the one hand, structured activites reduce victimization risk due to, for example, amplified supervision, social control, and a more protective environment. Unstructured activities, on the other hand, entail a higher risk of victimization because, for example, people are more frequently placed in close proximity to motivated offenders or more exposed to hazardous situations.

In the later conditional models, two indicators derived from the lifestyle-routine activity framework are included in the analysis as time-invariant predictors of the dynamic relationship between victimization and offending. Specifically, we consider activities with peers that reflect *unstructured* and *structured socializing*. For measuring the activities, the respondents were asked how much certain statements apply to their friend group, each on a five-point Likert scale where higher values represent a higher frequency of the considered activity. The activities were measured at every age under study. Correlations show that the activities are mostly stable over the considered age span[5], thus, we averaged the values over the seven-year-period to obtain a single, time-invariant indicator as also practiced in previous studies (Erdmann & Reinecke, 2021; Labouvie, Pandina, & Johnson, 2016; Mulford et al., 2018).

For the unstructured activity, we use an indicator labeled as *partying* which consists of the two highly correlated items *alcohol consumption* ("When we are together, we drink a lot of alcohol.") and *going out* ("We visit bars, discotheques, or concerts together."), both measured on a five-point Likert scale from "does not apply" to "fully applies". Alcohol use has shown to be a consistent predictor of both delinquency and victimization (Engström, 2018; Felson & Staff, 2010; Mustaine & Tewksbury, 2000). Also, going to parties has regularly been considered an unstructured activity (Osgood et al., 1996). Thus, the indicator *partying* is suspected to facilitate both offending and victimization.

As a structured activity, we consider *studying* ("We study together for (vocational) school", measured on a five-point Likert scale from "does not apply" to "fully applies"). We expect this activity to have a mitigating effect on crime and victimization. This anticipation is based on the theoretical presumption that spending time in structured activites leaves less time available to conduct crime on the one hand (Osgood et al., 1996) and reduces exposure to potential offenders on the other hand.

5 The frequency of an activity at a certain age correlates strongly with the frequency of the same activity one year later (r between 0.44 and 0.66).

Descriptive Results

Table 1 shows the annual incidence rate of victimization and offending (mean and variance) for every age using the seven-wave panel data. At the age of 14, the mean incidence of victimization has an average frequency of 0.61 which drops down to 0.11 at the age of 20.

The variance of victimization decreases from 4.05 to 0.54 because the amount of zeros (i.e., no victimization) increases. A very similar development holds for general offending. The mean annual incidence is higher for offending than for victimization partly due to the higher number of different offenses included. At the age of 14, the mean incidence of offending has an average frequency of two offenses (2.05). At 20 years of age, the mean incidence drops down to 0.35. Also the variance decreases from 14.96 to 2.80 due to the increasing amount of zeros (i.e., no offenses). As expected, incidence rates of victimization and offending decrease throughout the phase of adolescence reflecting a parallel process of development.

Table 2 shows the descriptive results for the independent variables gender and peer activities. The panel data contains a somewhat higher percentage of females compared to males. The averaged distributions of the peer activities reflect a balanced activity pattern.

Table 1 Descriptive Results for Violent Victimization and General Offending

	Victimization				Offending			
Age	N	Mean	Var.	% Zero	n	Mean	Var.	% Zero
14	2201	0.61	4.05	83.2	2208	2.05	14.96	66.4
15	2406	0.47	2.89	85.0	2422	1.98	15.22	69.2
16	2563	0.40	2.45	87.1	2568	1.54	12.31	74.5
17	2480	0.36	2.25	88.7	2484	1.19	9.94	80.3
18	2435	0.23	1.53	92.0	2436	0.71	5.84	86.5
19	2455	0.15	0.84	94.0	2457	0.47	3.70	90.3
20	2436	0.11	0.54	95.1	2439	0.35	2.80	92.6

Note. Mean and variance of incidences for violent victimization and general offending, percentages of zero for each panel wave. Results are based on seven-wave panel, n = 2679, maximum of two missing wave information, full information maximum likelihood for estimating means and variances, and values rounded to two decimal digits.

Table 2 Descriptive Results for Gender and Peer Activity Variables

Gender	n	Proportion	
female	1469	0.55	
Male	1207	0.45	
Peer Activities	**n**	**Mean**	**Var.**
Partying	2600	2.66	0.89
Studying	2598	2.71	0.88

Note. Proportions of gender, means and variances for peer activities, based on seven-wave panel, n = 2679, maximum of two missing wave information, full information maximum likelihood for estimating means and variances, and values rounded to two decimal digits.

Model Specifications and Results

Unconditional and Conditional Model Specifications

According to the general specification of the CTSEM (Equation 1) the unconditional model contains the time-variant variables offending (off) and victimization (vict):[6]

$$d\begin{bmatrix} off \\ vict \end{bmatrix}(t) = \left(\begin{bmatrix} a\_off & a\_off\_vict \\ a\_vict\_off & a\_vict \end{bmatrix}\begin{bmatrix} off \\ vict \end{bmatrix}(t) + \begin{bmatrix} k\_cint1 \\ k\_cint2 \end{bmatrix}\right) dt + \\ cholsdcor\left\{\begin{bmatrix} q\_off & 0 \\ q\_vict\_off & q\_vict \end{bmatrix}\right\} d\begin{bmatrix} W_1 \\ W_2 \end{bmatrix}(t)$$

with initial latent state

$$\begin{bmatrix} off \\ vict \end{bmatrix}(t_0) \sim N\left(\begin{bmatrix} T0m\_off \\ T0m\_vict \end{bmatrix} covsdcor\left\{\begin{bmatrix} T0var\_off & 0 \\ T0var\_vict\_off & T0var\_vict \end{bmatrix}\right\}\right)$$

The CTM contains four parameters in drift matrix A, two parameters in vector b (intercepts) and three parameters in matrix Q for the diffusion process. Five parameters (two means, two variances and one covariance) are estimated for the initial latent state of the process. In previous analyses with latent growth and cross-lagged panel models Erdmann and Reinecke (2018) showed that the developments

6 *cholsdcor* converts lower triangular matrix of standard deviation and unconstrained correlation to Cholesky factor covariance, see Driver & Voelkle (2018: 11). *covsdcor* is the transposed cross product of *cholsdcor* which renders the stationary covariance matrix.

of offending and victimization are highly parallel processes that reflect similar stability and mutual influence over the time of adolescence. Therefore, it is intended to explore how the autoeffects differ between offending and victimization and how large would be the particular crosseffects. Absence of a particular crosseffect can be tested by restricting the particular parameter in the off-diagonal of drift matrix *A* to zero. A test of equal crosseffects would show that both processes are influencing each other with the same strength. Results of the different model specifications are shown and discussed in the next section.

The measurement part of the CTM (Equation 2) contains factor loadings (λ) which are fixed to 1.0. Measurement error variances (ε) and manifest intercepts (τ) are fixed to zero. For any different model specification regarding the elements of matrix *A*, there are no parameter to be estimated for the measurement model (cf. Voelkle et al., 2012).

As defined in the section Continuous Time Structural Equation Modeling, vector *b* contains the effects of the time independent predictors *z* (i.e., gender and indicators of routine activities) on the parameters of interest. Below, vector β is shown for the predictor gender:[7]

$$\beta = \begin{bmatrix} b\_T0m\_off \\ b\_T0m\_vict \\ b\_cint1 \\ b\_cint2 \\ b\_a\_off \\ b\_a\_off,vict \\ b\_a\_vict\_off \\ b\_a\_vict \end{bmatrix} [Gender]$$

The first two parameters are the effects of gender on the means of offending and victimization at the initial time point followed by the two parameters indicating the effects of gender on the intercepts of offending and victimization. The last four parameters consider the effects of gender on the parameters of the drift matrix *A*. For example, the parameter $b_{a_{off}}$ is the regression of gender on the autoeffect of offending.

The same specification of vector β was used for the variables of routine activities (partying and studying). Because of the complexity of the conditional CTM, the influence of the time independent predictors are considered in separate analyses.

7 Note, that not *all* possible parameters are included in vector β. For example, effects on the parameters of the diffusion matrix *Q*could be added. This was not done, because no theoretical reasons exist to justify these specifications.

Model Results

According to the propositions above, all models are estimated with the R package `ctsem` (Driver & Voelkle, 2018, 2021) using data from the seven panel waves of the CrimoC study. Maximum likelihood estimation procedure is used for the particular model estimation, prior information is not specified.[8]

Unconditional Models

Table 3 gives an overview about the log-likelihoods and the information criteria AIC and BIC (Kuha, 2004) for the estimated unconditional models.[9]

Model A contains the measurements of offending and victimization with full specification of the drift matrix. Model B restricts the crosseffect from offending to victimization to zero, Model C alternatively restricts the crosseffect from victimization to offending to zero. Therefore, both restricted unconditional Models B and C have the same number of parameters and one parameter less than Model A. Alternatively, Model D considers the restriction of equal crosseffects ($a_{off,vict} = a_{vict,off}$). Comparing the AIC across the four model variants, Model A has the lowest value. Comparing the BIC, Model D has the lowest value. But the difference of the BIC values between Model A and D is quite small. Therefore, Model A is chosen and will be described in more detail.

Table 3 Log-Likelihood and Information Criteria for Unconditional CTMs

Unconditional CTMs	Par.	- log (L)	AIC	BIC
Model A (unrestricted)	21	-70032.27	140106.5	140230.30
Model B (restricted) (Off→Vict = 0)	20	-70088.71	140217.4	140335.28
Model C (restricted) *(Vict→Off = 0)*	20	-70046.71	140133.4	140251.28
Model D (restricted) (Off→Vict = Vict→Off)	20	-70035.99	140112.0	140229.84

8 CTMs are estimated using the command `ctStanFit` with longformat data. Driver & Voelkle (2021: 894) recommend for the maximum likelihood approach to set the argument `nopriors=TRUE` in the command `ctStanFit` to disable the priors.

9 In the current version of the R package `ctsem`, only the AIC is provided. In addition, the BIC was calculated.

Table 4 Parameter Estimates of the Unconditional CTMs

	Model A		Model B		Model C		Model D	
Parameter	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD
Drift Matrix (A)								
$a_{off,\ off}$	-1.061	0.040	-1.085	0.035	-0.976	0.029	-1.013	0.030
$a_{off,vict}$	0.569	0.111	0.280	0.093	-	-	0.285	0.034
$a_{vict,off}$	0.286	0.034	-	-	0.246	0.030	0.285	0.034
$a_{vict,vict}$	-2.598	0.140	-2.242	0.095	-2.595	0.136	-2.619	0.142
Intercepts (b)								
k_{off}	0.772	0.053	0.895	0.055	0.853	0.049	0.806	0.050
k_{vict}	0.416	0.048	0.632	0.043	0.464	0.049	0.426	0.048
Diffusion Matrix (Q)								
q_{off}	15.039	0.324	15.359	0.333	14.799	0.307	14.869	0.295
q_{vict}	7.546	0.366	6.906	0.268	7.564	0.363	7.603	0.373
$q_{off,vict}$	0.276	0.228	1.773	0.158	1.113	0.147	0.615	0.255
Initial Occasion								
$T0m_{off}$	2.223	0.084	2.213	0.082	2.218	0.082	2.222	0.084
$T0m_{vict}$	0.658	0.043	0.653	0.043	0.647	0.043	0.653	0.041
$T0var_{off}$	16.222	0.482	16.115	0.512	16.214	0.508	16.187	0.492
$T0var_{vict}$	4.153	0.129	4.150	0.126	4.126	0.123	4.136	0.122
$T0var_{off,vict}$	2.713	0.200	2.656	0.184	2.630	0.224	2.657	0.207

SD = Standard Deviation

According to the diagonal elements of the drift matrix (Model A, cf. Table 4), both processes are approaching an equillibrium in the future. The process is faster for victimization compared to offending (|–2.598| > |–1.061|). The off-diagonal elements of the drift matrix show that the impact of victimization on offending is stronger than the impact of offending on victimization (|0.569| > |0.286|).

The corresponding discrete time parameters can be computed at any arbitrary point in time. For time interval $\Delta t = 1$ autoregressive and cross-lagged discrete time parameters are calculated as follows:[10]

$$A(\Delta t) = e^{A\Delta t} = e^{\begin{pmatrix}-1.061 & 0.569\\ 0.286 & -2.598\end{pmatrix}\cdot 1} = \begin{pmatrix}0.364 & 0.103\\ 0.051 & 0.086\end{pmatrix}$$

10 In the R package `ctsem` the argument `ctStanContinuousPars` can be used to calculate the discrete time parameters (Driver & Voelkle, 2021).

The transformation is unique under the condition that the eigenvalues of $A(\Delta t)$are real and have eigenvalues between zero and one (Kuiper & Ryan, 2018).

The calculated autoregressive discrete-time parameters show that victimization is less stable compared to offending ($|0.086| < |0.364|$). The cross-lagged parameters show that the impact of victimization on offending is stronger than the impact of offending on victimization ($|0.103| > |0.052|$). Restricting the latter cross-lagged effect to zero does not lead to an overall model improvement (cf. Model B in Table 3).

Furthermore, the R package `ctsem` allows a visual inspection of the development of victimization and offending over time and the relationship between both processes. Based on the estimates of the drift matrix (cf. Model A in Table 4), the autoeffect plots are shown in Figure 2. Estimates of the autoeffects are obtained by sampling from the subjects data. The red line shows the autoeffect process of offending, the turquoise line shows the same process of victimization. Over the time-interval on a range from 0 to 5 the processes are approaching asymptotically zero. As the curves show this is faster for victimization compared to offending meaning more changes for offending occur in future time periods. Since there are stable and stationary processes, there is an equilibrium to which the processes will return.

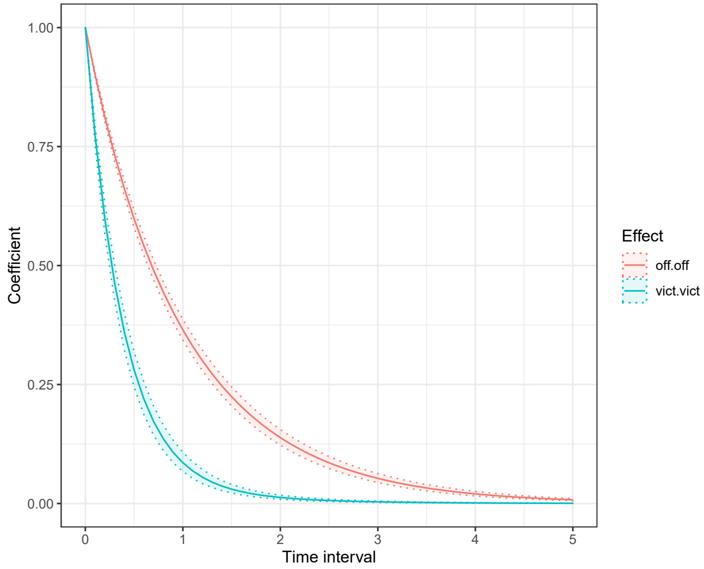

Figure 2 Autoeffect Plot of Victimization and Offending

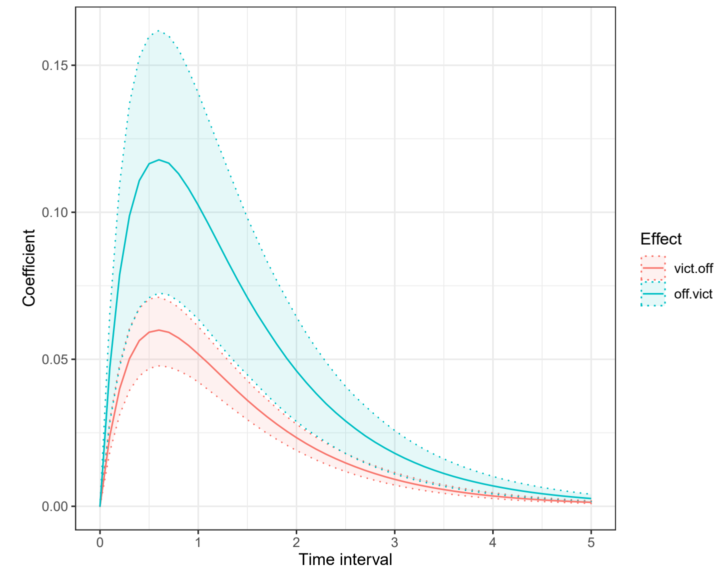

Figure 3 Crosseffect Plot of Victimization and Offending

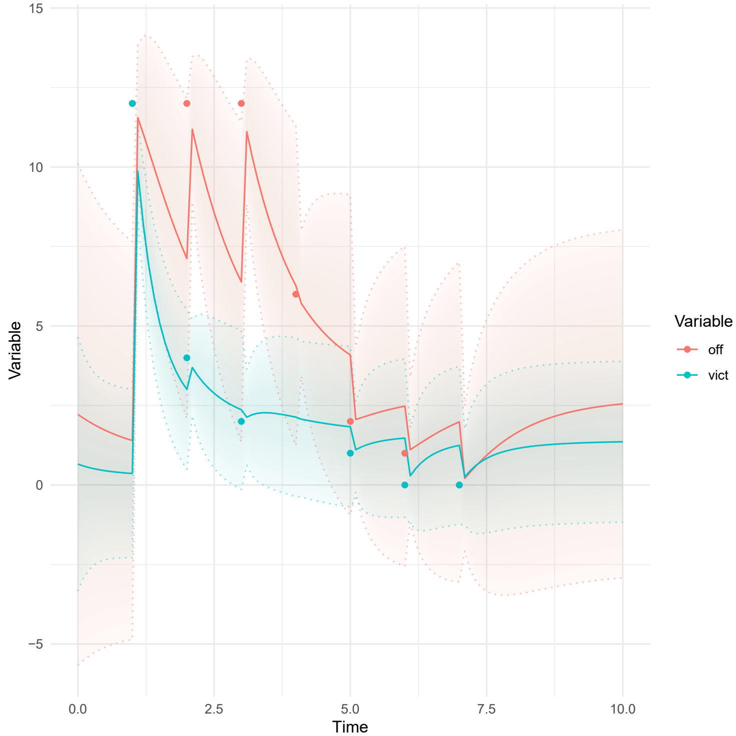

Figure 4 Prediction Plots for Subject 5

Crosseffects of offending and victimization are shown in Figure 3. For short time intervals the impact of victimization on offending (turquoise line) is larger than the impact of offending on victimization (red line). When the time interval becomes very large, the relationships dampens out.

For individual level analysis, Figure 4 shows observed and predicted scores for a particular person (Subject 5) obtained from the Kalman filter (Driver & Voelkle, 2018).[11]

The red line (offending) reflects higher score estimates on offending during adolescence (first panel waves) and lower scores later on. The green line reflects also some high scores on victimization but lower compared to offending. After the last panel wave, the Kalman filter estimates extrapolated future values.

Conditional Models

Table 5 summarizes the conditional models with gender and routine activities (partying and studying) as time independent predictors. Because of the model complexity, each time independent predictor is considered separately for the particular CTM. In the baseline versions of the conditional CTMs, eight regression parameters are estimated (cf. vector β in Section *Unconditional and Conditional Model Specifications*). Some of these regression estimates are low and not significant.

In the restricted versions of the conditional models, the non-significant regression parameters are restricted to zero for reasons of parsimony. When comparing the particular baseline models with the restricted ones (e.g., Model E with Model F for the time independent predictor gender), the information criteria AIC and BIC of the restricted models have always slightly lower values. In the following paragraphs, the results of the conditional models are discussed with emphasis towards the influences of the particular time independent predictor.[12]

Gender. Effects (vector β) of gender on the model parameters are summarized in Table 6 (Models E and F). Two parameters are restricted to zero in Model F: The effects of gender on the intercept of offending and victimization ($b_{k_{off}}$, $b_{k_{vict}}$).

11 The Kalman Filter produces subject specific estimates of the process variables based on all prior and current observations. It provides also a prediction of the future system state based on past estimations. In the R package `ctsem` predicted scores can be computed via the argument `ctKalman` (Driver & Voelkle, 2021).

12 In the conditional models the parameter estimates of the drift matrix, of the intercepts, of the diffusion matrix, and of the initial occasions do not differ substantially compared to the ones obtained by the unconditional models (cf. Table 4). Therefore, these estimates are not reported again.

Table 5 Log-Likelihood and Information Criteria for Conditional CTMs

Model variants	Par.	- log (L)	AIC	BIC
Model E (Gender)	29	-69089.98	138238.0	138408.9
Model F (Gender)	27	-69091.24	138236.5	138398.0
Model G (Party)	29	-66550.92	133159.8	133330.7
Model H (Party)	28	-66551.49	133159.0	133324.0
Model I (Study)	29	-67229.62	134517.2	134688.1
Model J (Study)	27	-67230.59	134515.2	134674.3

Table 6 Parameter Estimates of the Effects of Gender

	Model E			Model F		
Parameter	Estimate	SD	z	Estimate	SD	z
Effects on Drift Matrix (A)						
$b_{a_{off,off}}$	1.133	0.060	18.80	1.130	0.066	17.08
$b_{a_{off,vict}}$	-0.495	0.171	-2.89	-0.412	0.149	-2.77
$b_{a_{vict,off}}$	-0.222	0.050	-4.43	-0.238	0.052	-4.61
$b_{a_{vict,vict}}$	2.123	0.147	14.39	2.095	0.193	10.88
Effects on Intercepts (b)						
$b_{k_{off}}$	0.112	0.085	1.33	-	-	-
$b_{k_{vict}}$	-0.102	0.094	-1.09	-	-	-
Effects on Initial Occasion						
$b_{T0m_{off}}$	0.905	0.166	5.45	0.871	0.172	5.06
$b_{T0m_{vict}}$	0.475	0.084	5.66	0.474	0.091	5.19

SD = Standard Deviation; z = z-value

Positive values of the regression estimates indicate higher values for males, negative values indicate higher values for females. In Model E and Model F regression coefficients for the elements of drift matrix A and means of the initial occasion are similar. Gender differences are higher for the autoeffect of victimization (Model E: 2.12, Model F: 2.10) compared to the autoeffect of offending (Model E/F: 1.13). The opposite gender difference can be observed for the crosseffects. Gender differences are higher for the crosseffect of victimization to offending (Model E: -0.50; Model F: -0.41) compared to the reversed crosseffect (Model E: -0.22; Model

F: -0.24). Higher gender differences are observed for the initial mean of offending (Model E: 0.91; Model F: 0.87) compared to the ones for the initial mean of victimization (Model E: 0.48; Model F: 0.47).

Figure 5 shows how the expectations for individuals parameter values change as a function of the particular value of the time independent predictor gender (Driver & Voelkle, 2021: 898). Four discrete time parameters of matrix A (dtDrift) based on the estimates of Model F are included in the graph. For males (-axis value of one) the likelihood of change for the autoregressions of offending (red line in the graph) and victimization (violet line in the graph) is higher compared to females (-axis value of zero). Gender differences are to be expected much higher for offending compared to victimization. The likelihood of change for both crossregressions (blue line: effect of victimization to offending; green line: effect of offending to victimization) is similar but on different levels. Note, that the effects of gender on both intercepts are restricted to zero in Model F and therefore not included in the graph (cf. Table 6).

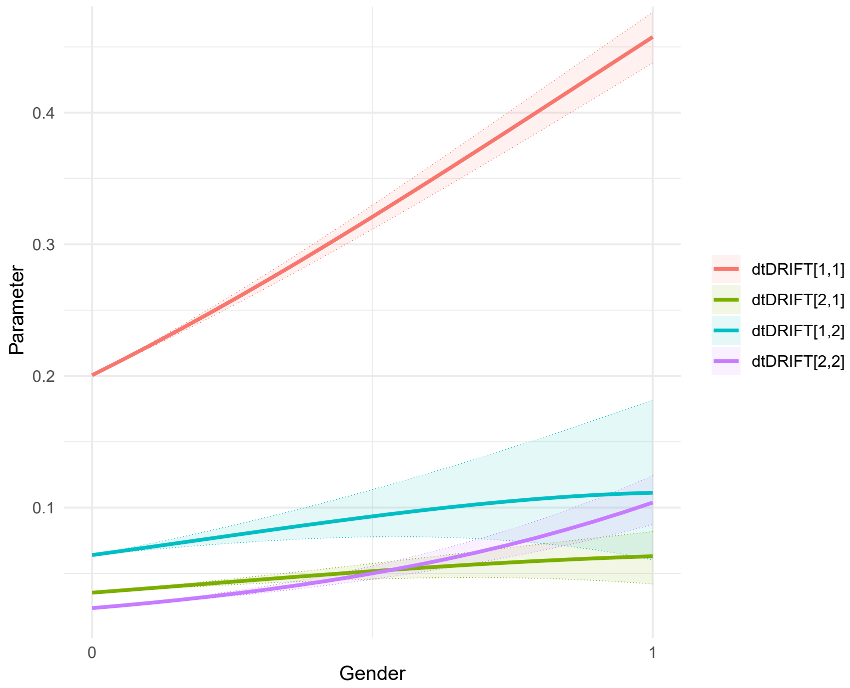

Figure 5 Expected Parameter Values as a Function of Gender. The four lines correspond to the four elements of the drift matrix. To ease interpretation, the discrete time parameters (dtDRIFT) for a time interval of 1 are presented.

Table 7 Parameter Estimates of the Effects of Partying

	Model G			Model H		
Parameter	Estimate	SD	z	Estimate	SD	z
Effects on Drift Matrix (A)						
$b_{a_{off,off}}$	1.520	0.040	37.67	1.531	0.061	25.00
$b_{a_{off,vict}}$	-0.511	0.099	-5.17	-0.492	0.099	-4.99
$b_{a_{vict,off}}$	-0.062	0.031	-2.00	-0.075	0.032	-2.30
$b_{a_{vict,vict}}$	2.221	0.103	21.62	2.248	0.203	11.06
Effects on Intercepts (b)						
$b_{k_{off}}$	0.069	0.061	1.13	-	-	-
$b_{k_{vict}}$	-0.155	0.069	-2.25	-0.141	0.066	-2.15
Effects on Initial Occasion						
$b_{T0m_{off}}$	1.246	0.086	14.56	1.228	0.020	14.76
$b_{T0m_{vict}}$	0.292	0.050	5.85	0.289	0.040	12.23

SD = Standard Deviation; z = z-value

Routine Activity: Partying Effects (vector β) of the routine activity partying on the model parameters of offending and victimization are summarized in Table 7 (Models G and H).

One parameter is restricted to zero in Model H: The effect of partying on the intercept of offending ($b_{k_{off}}$).

Regarding Models G and H, the regression estimates are positive for the diagonal elements of Matrix A (Model G: 1.52 and 2.22; Model H: 1.53 and 2.25): With more party activities, the autoeffects of offending and victimization increase. For the crosseffects, the regressions of partying are both negative in the particular models (Model G: -0.51 and -0.06; Model H: -0.49 and -0.08). The intercept of offending will be slightly higher for persons with higher party activities (Model G: 0.07) but these estimate turns to be not significant and is restricted to zero in Model H. The regression of the intercept of victimization on partying remains significant (Model G: -0.16; Model H: -0.14) meaning that this intercept will be lower for persons with higher party activities. For the means of the initial occasion of offending and victimization, positive and significant regressions of partying can be observed (for offending in Model G: 1.25 and in Model H: 1.23; for victimization in Models G and H: 0.29). At the beginning of the developmental process persons with more party activities are likely to have more offending and victimization experiences.

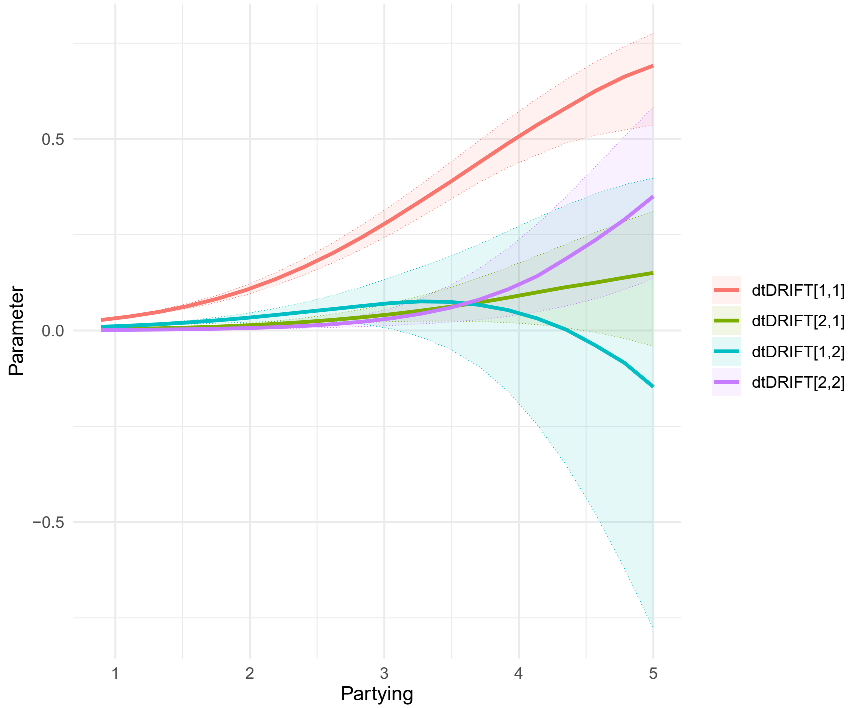

Figure 6 Expected Parameter Values as a Function of Partying. The four lines correspond to the four elements of the drift matrix. To ease interpretation, the discrete time parameters (dtDRIFT) for a time interval of 1 are presented.

Figure 6 shows how the expectations for individuals parameter values change as a function of the time independent predictor partying. It has a large effect on the autoeffect of offending (red line) compared to the autoeffect of victimization (violet line). With increasing party activities, it is likely that the developmental process of offending and victimization will change more often. That means that with extreme high numbers of party activities the developmental process of offending is likely to change (red line). The expected values of partying on the crosseffect between offending and victimization (green and blue line) are somewhat lower. For the crosseffect of offending on victimization a dampening effect can be observed (blue line).

Table 8 Parameter Estimates of the Regression on Studying

	Model I			Model J		
Parameter	Estimate	SD	z	Estimate	SD	z
Effects on Drift Matrix (A)						
$b_{a_{off,off}}$	-0.228	0.014	-16.92	-0.230	0.013	-17.85
$b_{a_{off,vict}}$	0.587	0.166	3.53	0.520	0.217	2.40
$b_{a_{vict,off}}$	0.181	0.052	3.46	0.197	0.043	4.62
$b_{a_{vict,vict}}$	-0.908	0.150	-6.04	-0.879	0.150	-5.85
Effects on Intercepts (b)						
$b_{k_{off}}$	-0.058	0.057	-1.03	-	-	-
$b_{k_{vict}}$	0.098	0.078	-1.25	-	-	-
Effects on Initial Occasion						
$b_{T0m_{off}}$	-1.004	0.084	-11.97	-0.989	0.086	-11.50
$b_{T0m_{vict}}$	-0.210	0.045	-4.66	-0.209	0.046	-4.55

SD = Standard Deviation; z = z-value

Routine Activity: Studying Effects of routine activity studying (vector β) on model parameters are summarized in Table 8 (Models I and J). Two parameters are restricted to zero in Model J: The regression of the intercept of offending (k_{off}) and victimization (k_{vict}) on partying.

Regarding Models I and J the regression estimates are negative for the diagonal elements of Matrix A (Model I: -0.23 and -0.91; Model J: -0.23 and -0.88): With more activities to study, the autoeffects of offending and victimization decrease. For the crosseffects, the regressions of studying are both positive in the particular models (Model I: 0.58 and 0.18; Model J: 0.52 and 0.20). The influences on the intercepts of offending and victimization are not significant and the parameters are restricted to zero in Model J. For the means of the initial occasion of offending and victimization, negative and significant regressions of studying can be observed (for offending in Model I: -1.00 and in Model J: -0.99; for victimization in Models I and H: -0.21). At the beginning of the developmental process persons with more study activities are likely to have less offending and victimization experiences.

Figure 7 shows how the expectations for individuals parameter values change as a function of the time independent predictor studying. Similar to partying, it has a large impact on the autoeffect of offending (red line) compared to the autoef-

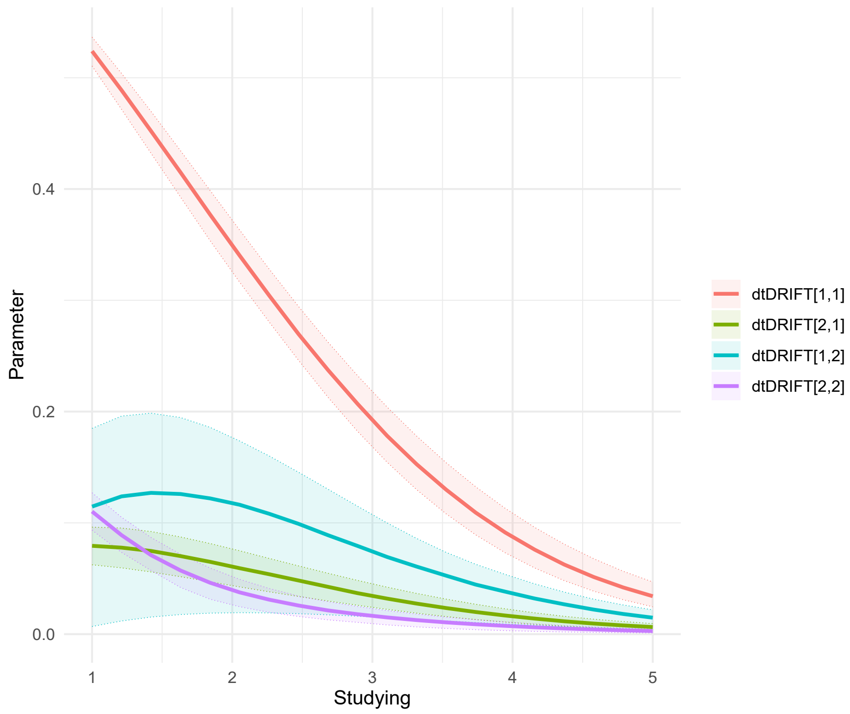

Figure 7 Expected Parameter Values as a Function of Studying. The four lines correspond to the four elements of the drift matrix. To ease interpretation, the discrete time parameters (dtDRIFT) for a time interval of 1 are presented.

fect of victimization (violet line). But the direction of the expected values is completely opposite in comparison to partying (cf. Figure 6). With increasing activities to study, it is likely that the developmental process of offending will change less. This means that with low study activities, the developmental process of offending is likely to change (red line). In principle, the expected value change for victimization goes into the same direction but on a much lower level. The expected values of studying on the particular crosseffects between offending and victimization (green and blue line) are positive. The values reflect a dampening effect of studying.

5 Discussion

Several advantages of stochastic differential equation models for the social and behavioral sciences have been adressed and discussed in the statistical literature for decades. Foremost is the use of time for the modeling process. Discrete-time methods are often used although the underlying longitudinal processes require models based on continuous time. In their editorial introduction to a special issue on continuous time modeling of panel data, Oud and Singer (2008, p. 1) remark that the use of discrete-time models might work as long as the time interval in the data is small (e.g., time-series data). But in the social and behavioral sciences panel data with far less measurement frequencies than observations are more common. It has been shown that in widely used cross-lagged panel models the results are inherently bound to the time intervals of the panel data (e.g., Delsing & Oud, 2008; Voelkle et al., 2012). More and more large-scale panel studies employ different time intervals due to substantive reasons or financial restrictions and researchers have to cope with such designs when analyzing the data.

Continuous time models on the basis of stochastic differential equations can overcome limitations of standard autoregressive models like the cross-lagged panel model. We have briefly shown the relationship between estimated parameters of the continuous-time model (auto- and crosseffects in the drift matrix A) and the corresponding discrete-time parameters in the autoregressive cross-lagged matrix $A^{*}_{\Delta t_u}$ (cf. Equation 1 and 3). Discrete and continuous time parameters are directly available during estimation and it is possible to transform the parameters of an estimated continuous time model to the discrete time parameters for any time interval.

Continuous time models are implemented in the R package `ctsem` which has been used here to study the long-term relationship between victimization and offending during the age of adolescence. Unconditional as well as conditional models are estimated. The parameters of the unconditional models show that the process of victimization is less stable compared to offending while the impact of victimization on offending is stronger than the impact of offending on victimization. The particular crossregression plot shows that this impact holds for the phase of early adolescence (14 to 16 years of age) but tends to diminish later (Figure 3).

Gender as well as unstructured and structured routine activities (partying and studying) are used as time independent predictors in the conditional models. Gender differences are higher for the autoregression of victimization compared to the autoregression of offending. In both cases, males would have larger negative values in the diagonal of the drift matrix meaning that the process is more unstable and refers to a larger amount of activities. Individual parameter change is more likely for males compared to females (Figure 5). A similar picture can be observed for the unstructered routine activity *partying*. The more party activities are observed the higher is the instability of the developmental process of offending and victimization. The tendency for individual parameter value change is increasing (Figure 6). For the structured routine activity *studying*, the opposite result is gained from the model estimates. With more study activities the developmental process of offending and victimization is becoming more stable.

The tendency for individual parameter value change is constantly decreasing (Figure 7).

These results support previous findings that the risk for males to be in a group of victimized high-level offender is much higher compared to females (cf. Erdmann & Reinecke, 2021). In addition, group activities like meeting with friends, partying and hanging out with friends also increased the risk to be a victimized high-level offender whereas studying with friends has a decreasing impact.

Like in the previous publications of Erdmann and Reinecke (2018, 2021), the panel data of the CrimoC-study used here contains seven panel waves limited to persons who participated at minimum in five out seven waves (n=2679). We also tested the models using all persons for the particular time interval between 2003 and 2009 (cf. Figure 1) including those who participated less than five times (n=4076). No substantive differences in model parameters compared to the reported ones could be detected.

Of course, the application of continuous time models with criminological panel data has some limitations. The dependent variables offending and victimization are summed indices of annual incidences. So, we treated both variables without specifying a measurement model (cf. Equation 2). Furthermore, the dependent variables are treated as continuous measurements although they are based on count data (number of incidences per year). For count measurements other link function for estimating a CTSEM should be used like the Poisson or the negative binomial model (Hilbe, 2011). But unfortunately, these link functions are not yet implemented in the R package `ctsem` (but see Hecht et al., 2019).

We explored the impact of the time independent predictors one by one instead of using them simultaneously in a single conditional CTSEM. This was done for substantive reasons as well as to reduce the model complexity, but does not consider potential dependencies among the predictors.

Although fully Bayesian approaches are implemented in the current version of the R package `ctsem` (Driver & Voelkle, 2018), we restricted ourselves to maximum likelihood estimation, respectively maximum a posteriori estimates. This was done for reasons of computation time. Comparing our approach and the empirical results to a fully Bayesian analysis with Hamiltonian Monte Carlo sampling as implemented in Stan (Carpenter et al., 2017) would be an interesting future research direction.

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