PARTICIPATION AND FREQUENCY DURING CRIMINAL CAREERS OVER THE LIFE SPAN[1]

Hanno Petras
University of Maryland College Park

Paul Nieuwbeerta
NSCR

Alex R. Piquero
University of Maryland College Park

Wednesday, August 12, 2009

1

Abstract

Recent advances and debates surrounding general/developmental and static/dynamic theories of crime can be traced to the 1986 National Academy of Science Report on criminal careers and the discussion it generated. A key point of contention lies in the interpretation of the age-crime curve. For Gottfredson and Hirschi, the decline in the age-crime curve in early adulthood reflects decreasing individual offending frequency (λ) after the peak. Blumstein et al. claim that the decline in the aggregate age-crime curve can also be attributable to the termination of criminal careers, and the average value of λ could stay constant (or increase with age) for those offenders who remain active after that peak. Using data from the Criminal Career and Life Course Study - including information on criminal convictions over 60 years of almost 5,000 persons convicted in the Netherlands - and applying a Two-Part Growth Model that explicitly distinguishes between participation and frequency - the paper assesses the participation/frequency debate. Results suggest that the decline in the age-crime curve in early adulthood reflects both decreasing individual offending participation and frequency after the peak, that the probabilities of participation and frequency are significantly related at the individual level, and that sex and marriage influence both participation and frequency.

2

INTRODUCTION

Many early studies on criminal careers have become classics in criminology (Sutherland 1939; Glueck & Glueck 1950; Shaw 1930), and the publication of the 1986 National Academy of Science Report on criminal careers (Blumstein et al. 1986) re-invigorated the study of criminal careers and generated much debate (Barnett et al. 1989; Blumstein, Cohen & Farrington 1988a, 1988b; Gottfredson & Hirschi 1986, 1988; Rowe et al. 1990; Nagin & Smith, 1990; Greenberg 1991; Land 1992; Osgood & Rowe 1994). The report defined the criminal career as the longitudinal sequence of crimes committed by an individual offender, and outlined the basic conceptual tools and vocabulary, providing the framework for many current theoretical debates in Developmental/Life Course Criminology (Farrington 2003).

A key claim made in the report was that it is important to carry out longitudinal research in order to answer critical questions about criminal career patterns, including the important distinction between the participation (*prevalence*) of offending and the frequency (*incidence*) of crime. Participation refers to the proportion of a population who are active offenders at any given time, while frequency refers to the average annual rate at which this subgroup of active offenders commits crimes. Frequency characterizes the intensity/rate of crimes of individual offenders and is often denoted by lambda (λ).

The authors claimed that the distinction between participation and frequency is especially relevant when studying the age-crime relationship. As they argue, the well-known aggregate age crime curve could result both from age-graded differences in participation (more adolescents than adults actively involved in crime) and from age-graded differences in frequency. On this point, they argued that the relationship with age

3

of these two criminal career features differed: participation varied with age – in a way similar to the aggregate age-crime curve – but frequency was stable over time and increased with age for certain types of crime and subgroups of offenders (Farrington 1986; Laub & Sampson 2003:16). Finally, in distinguishing between participation and frequency, the possibility was raised that theories of crime may require separate explanations for the two dimensions because the factors stimulating individuals to become involved in crime may be different from the factors affecting the frequency with which active offenders commit crimes (Blumstein, Cohen & Farrington 1988a,b).

The distinction between participation and frequency was not entirely embraced among criminologists. Gottfredson and Hirschi outlined a static view claiming that the age-crime relationship observed at the aggregate level mirrors that at the individual level – all individuals showing a rise and decline in crime *frequency* as they aged. Gottfredson and Hirschi explicitly deny the need to distinguish between participation and frequency, because both reflect the same underlying criminal propensity. Obviously, this is an empirical question, but surprisingly this question has not received much empirical attention (Piquero, Farrington & Blumstein 2007:46-60).

Using data from the Criminal Career and Life Course Study (CCLS) - including information on criminal convictions over 60 years of almost 5,000 persons convicted in the Netherlands – and applying recently developed Two-Part Growth Models that distinguish explicitly between participation and frequency – we examine whether there is a meaningful empirical distinction between participation and frequency, as evidenced by their relationships to age, gender, and marriage. Such an analysis is important for three reasons. First, issues of participation and frequency have not been adequately addressed

in studies of the development of criminal activity. Second, the studies that have examined this distinction rely on longitudinal data that does not characterize the full sequence of criminal careers, and has only focused on either the juvenile or the adult period, and rarely both (Sampson & Laub 2003). Finally, almost no research has employed non-US-based data.

BACKGROUND

The criminal careers debate has been described as a "watershed event", in that it stimulated the growth of research on crime and the life course generally (Osgood 2005:197), spurred several theories of crime that can be conceptualized across a wide spectrum that run the gamut from static to dynamic frameworks (Paternoster et al. 1997), and generated much attention among criminologists (Sampson & Laub 2005). In this regard, debates about whether general versus typological theories based on different predictions about onset and frequency and their causes have been prominent in the criminological literature. Yet, empirical research concerning the participation/frequency distinction over the lifespan has been scant, and is virtually non-existent with respect to whether life circumstances differentially relate to participation and frequency. Analysis investigating these issues would speak directly to this debate and may present a challenge to the typological hypothesis about the necessity of parceling out different parts (and causes) of criminal careers, or may present a challenge to more general frameworks about their view that participation and frequency resemble one another over the lifespan and are predicted by the same set of causes.

COMPETING HYPOTHESES ABOUT PARTICIPATION/FREQUENCY

Gottfredson and Hirschi explicitly deny the need to distinguish participation and frequency, because both reflect a similar underlying propensity. And while they do not deny that some offenders offend at a much higher rate than other offenders, they argue that offenders differ in degree and not kind; that is offenders can be arrayed on a continuum of criminal propensity, i.e., low self-control, with individuals at the higher end of the continuum (with lower self-control) evidencing higher criminal activity and vice versa. Importantly, Gottfredson and Hirschi do not permit the existence of qualitatively distinct offender groups; for them the decline in the age-crime curve in early adulthood reflects decreasing offending frequency (λ) after the peak. Gottfredson and Hirschi are clear in that the causes (i.e., any and all individual characteristics) of *both* participation and frequency are the same, and that life events, such as marriage, have no causal effect on the development of criminal careers (Hirschi & Gottfredson 1995).[2] Blumstein et al. instead argue that the participation/frequency dimensions may evince unique causes, contending that the reasons why individuals participate in crime *may* be different from the reasons why individuals either persist in crime or once active, commit crimes at a high frequency. They claim that for participation and frequency: (1) the relationships/effects of age may differ; (2) the effects of individual characteristics (sex) may differ; and (3) the effects of life circumstances (marriage) may differ.

In sum, while the two sides do not necessarily disagree about the basic pattern of relationships, they do disagree about their interpretations and implications. For instance,

---

[2] Even if Gottfredson and Hirschi were to grant that life events relate to criminal career dimensions, they would likely claim that the effect of such life events should be the same across all dimensions because of their view that studying distinct career dimensions is fruitless. Their general and purely static perspective can be contrasted against Sampson and Laub's general but dynamic theory which adopts the general theory approach that the specific course of offending across offenders is propelled by the same underlying causal processes, but departs from Gottfredson and Hirschi by allowing for *both* static and dynamic (life events) factors to relate to criminal activity over the lifespan, and that the relation of dynamic factors to criminal activity may be more or less salient at different points in the lifespan.

Gottfredson and Hirschi acknowledge that demographic differences on frequency tend to be smaller than on participation, but they argue that this is an artifact of selection rather than evidence of the necessity of distinguishing participation and frequency. Blumstein et al. would likely suggest that selection is not the penultimate explanation.

Extant theories make larger distinctions between participation and continuation but not necessarily between participation and frequency. For example, Gottfredson and Hirschi's theory would anticipate that self-control relates to both participation and frequency (i.e., those with low self-control are more likely to participate in crime, and once active engage in a higher frequency of crime). Other theories, such as labeling, would have more to say about why individuals commit crimes at a higher rate subsequent to their first crime as opposed to why individuals participate in crime in the first place.

There has been some empirical research on the participation/continuation issue (Piquero, Farrington, & Blumstein 2003), with some studies showing that the causes are different, some showing that the causes are the same, and others reporting a mixture of findings—with some unique effects for each of the respective dimensions (Smith et al. 1991; Nagin & Smith 1990; Paternoster & Triplett 1988; Piquero et al. 2007; Smith & Brame 1994). These studies have been limited to investigations of normative/community samples of adolescent youth followed for a short period of time (generally two to six years). Thus, it is unknown whether different samples, especially offender-based samples who evince much more offending than non-offender-based samples, followed well into adulthood would evince similar observations and patterns of relationships. This is no small matter for it is important to have a lengthy observation window as it allows for the

criminal career to 'play out' rather than offering a limited snapshot of community samples.

Only a small number of studies have investigated the participation/frequency distinction. For example, Rowe et al. (1990; Osgood & Rowe 1994) proposed a latent trait model that simultaneously accounts for both participation and frequency, and hypothesized that the parameters of the criminal career model could be accounted for by individual differences along a single, relatively stable dimension of crime proneness. Thus, individuals vary along this continuous dimension and their position on the dimension is somewhat stable over time (i.e., individuals higher in proneness obviously exhibit higher offending frequency). Their model asserts that discrete classes of criminals do not exist and that a single set of causal processes underlies the entire dimension. Their model fit both participation and frequency for several samples and measures of offending, supporting the idea that separate causal processes are un-necessary to account for group differences in frequency and participation. Greenberg (1991) employed a model that assumed that: (1) individuals were characterized by a mean offending rate, λ, that is constant over time; (2) criminal events occurred independently and at random (these two assumptions imply that the probability of an individual characterized by lambda is given by the Poisson distribution); and (3) but since all members were assumed to have the same λ, the third part of the model assumes that the populations of interest are heterogeneous with respect to λ. He found good support for his two-parameter model. Finally, Nagin & Smith (1990) addressed whether there were distinctive differences in the processes determining participation and frequency by developing several tests to examine not only whether the correlates of participation/frequency were similar but also

whether the same underlying statistical model was consistent with the data on both dimensions. Using data from the first two waves of the National Youth Survey, their results did not generally support the idea of distinguishing participation/frequency.

Taken together, these efforts have provided the basis for a knowledge base underlying the participation/frequency distinction, yet all remain limited in several respects, two of which are pertinent to the current study: the use of an offender-based sample followed for a long portion of the criminal career. The specific question investigated in the current study is whether there is a meaningful empirical distinction between participation and frequency, as evidenced by their relationships to individual characteristics and life circumstances. Below, we outline some potential possibilities.

Regarding *age*, analyses suggest that the rise and peak during mid to late adolescence is more a function of participation than frequency (i.e., more individuals offending rather than more offending among those who offend). Then, after late adolescence and into early/middle adulthood, offending tends to be a function more of the frequency of offending among those who are active than of many individuals participating. The key point is that as adulthood ensues, while a smaller number of individuals are offending (low participation) they tend to engage in a higher frequency of crimes (Farrington 1986; Laub & Sampson 2003).

Regarding *individual characteristics*, it has been found that certain characteristics exert different effects on participation and frequency. Blumstein and Graddy (1982) and Blumstein et al. (1986) find that sex and race exert strong effects on participation but not on recidivism/frequency (i.e., males and blacks were more likely to participate in crime, but once involved, the frequency of offending among whites and blacks and males and

females was similar). Several reasons for this finding have been put forth including: differential opportunity structures, different normative pressures, and neuropsychological, neurological, and biological differences. Others argue not necessarily that there are specific sex differences in the risk factors, but instead that there are differences in the average levels of the specific risk factors (differences in degree not kind; Moffitt et al. 2001). Then, once the hurdle for offending participation has been crossed, the initial differences tend to disappear because the individuals who remain and continue to commit many crimes evince many of the same type and level of risk factors.

Regarding *life circumstances* (marriage, employment, incarceration), theories differ on the expected effects. Whereas static theories predict no effects, dynamic theories permit effects. These latter theories however, are silent on whether there are differences across participation/frequency, but it would seem that there are reasons to think that there may be both similarities and differences. With respect to the similarities view, it may be that these life circumstances act in such a way as they close all crime opportunities as opposed to only limiting their frequency. Marriage limits the ability to associate with deviant peers and places constraints on time away from the marriage, which indirectly serves to reduce the chances of criminal activity and also to engage in many criminal activities. As a form of investment in conventional society, marriage and employment may also serve a social control function as individuals will not risk their roles in these social institutions by engaging in crime, regardless if it is one or many crimes.

CURRENT FOCUS

On one hand, it is surprising that the participation/frequency distinction has not received much empirical attention, especially because of the increase in longitudinal data

and research over the past twenty years (Farrington 2003; Laub & Sampson 2003; Piquero et al. 2003). Several new analytic methods especially designed to study offending trajectories (e.g., growth curve modeling and latent class growth analyses) have also become available (Kreuter & Muthén 2008; Nagin 2005; Muthén 2004; Piquero 2008), many of which have been applied to study participation and frequency over the lifespan.

On the other hand, it is less surprising that these issues have remained unaddressed, largely because the data requirements to study the question of the age-crime curve at the individual level are daunting. Longitudinal information of offending over a very long time period is needed, information on incarceration and death is necessary to control for 'false desistence' (Piquero et al. 2001), and since many individuals do not commit crime, in order to study offending frequency among active offenders information on a large number of individuals is required. Only a few studies can make a credible claim at having achieved these significant data requirements (Sampson & Laub 2003).

Another important reason why it is less surprising that the empirical study of the participation/frequency distinction has been little-investigated is that appropriate methods of analyses to study these features have only recently become available (Muthen 2001; Vermunt 2003). Most researchers studying criminal careers have applied hierarchical linear models (HLM), latent class growth analyses (LCGA) or growth mixture models (GMM). In these techniques, the dependent variable typically is a count of the number of crimes. Such analyses can only reveal that the 'average number of offenses' in the entire sample (HLM) or in each of the distinguished subgroups' (LCGA/GMM) change over time. The 'average number of offenses' here necessarily is a weighted average of the number of offenses committed by those individuals who do and those who do not commit

11

crimes. In other words, the rates of participation and frequency are merged together. Consequently, when applying these models, it remains unclear to what extent a decline in the age-crime curve may be attributable to the termination of criminal careers (i.e., changes in participation), or to a decrease in the number of offenses for those offenders who remain active (i.e., changes in frequency) (Blumstein 2005). It has only been recently that specific methodological techniques have been developed that afford an opportunity to critically examine this important criminal career distinction (Muthen 2001; Olsen & Schaefer 2001), but the requisite empirical analyses have not been undertaken.

This study builds on and expands previous research by employing long-term data and applying methods that have only recently become available in order to appropriately analyze participation/frequency over the lifespan. Specifically, this study uses criminal history data over a period of 38 years (i.e., age 12 to age 50) pertaining to a large sample of Dutch offenders. The data are analyzed using Two-Part Growth Models designed to distinguish participation and frequency. Based on extant theory and results from earlier work, we ask the following questions:

1. To what extent and in what way does age have (different?) effects on participation and frequency?

2. To what extent is participation and frequency related at the individual level?

3. To what extent are individual characteristics (sex) and life circumstances (marriage) related to participation and frequency?

DATA

To answer these questions data from the Criminal Careers and Life Course Study (CCLS) are analyzed (see Nieuwbeerta & Blokland 2003). This study is a large-scale

research project conducted by the Netherlands Institute for the Study of Crime and Law Enforcement and has been used to describe lifespan offending trajectories and the effects of life circumstances on these trajectories (Blokland, Nagin & Nieuwbeerta 2005; Blokland & Nieuwbeerta 2005). Court information and life course data were collected on 4,615 randomly selected individuals all convicted of a crime in 1977. Respondents were selected by means of a representative selection of 4% of all the criminal cases conclusively resolved in the Netherlands; they were cases where a judge pronounced a sentence and cases dismissed by the Public Prosecutor for reasons of policy or due to insufficient evidence. The advantage of a general national sample of this kind is that statements can be generalized to the total criminal population. Regarding personal characteristics of the individuals in the sample (see Blokland et al. 2005), a tenth of the respondents are women, a quarter of the respondents were younger than 20 in 1977, and half of them were between 20 and 35, their average age at the time was 27, four out of ten were unemployed, and the police arrest files referred to 37% of them as alcoholics and 2% as drug addicted.

Using extracts from the General Documentation Registry of the Ministry of Justice Court Documentation Service, a complete list of the criminal convictions incurred was drawn up at the beginning of 2003. The Documentation Registry contains information on all the criminal cases registered by Public Prosecutors in the Netherlands (not including crimes prosecuted abroad either before or after 1977). The regular extracts are supplemented by information on court cases not referred to in the extracts because of the period of limitation. Analyses only address the registrations of crimes the suspects were actually convicted for or dismissed by the Public Prosecutor for reasons of policy,

13

and are concisely referred to as convictions.[3] Data on incarceration were also obtained from the GDF extracts. Within each year-period, individuals were coded 'free on the street' for the proportion of the year that they were not incarcerated, with a minimum of one week per year to account for offenses perpetrated while on leave or detention in a semi-secure institution.[4]

Data on life circumstances were collected from population registration data (GBA). Since 1938 all citizens in the Netherlands are registered in their municipalities. Personal records in the population registration contain information on marriage and fertility history and date of death. Prior to electronic registration in 1994, personal record cards were used that were sent to the next town of living every time a person moved. For individuals who died before 1994 personal record cards were retrieved from the Centre for Genealogy and Heraldry. By 2002, 17% of the sample had died (Nieuwbeerta & Piquero 2008). Nearly three quarters of the final sample had been married at least once; 53% of these marriages ended in divorce. At age 19 about 10% were married, at age 25 about 50% were married, and at age 40 almost 70% were married.

A person-period file was constructed in which every record contained information on the number of convictions for each individual in each year, as well as information on all relevant covariates. Since only a few persons had reached an age over 72 by 2002

---

[3] Traditionally, frequency-of-conviction variables are treated as a count variable following a Poisson distribution (Osgood 2000), which is justified because the outcome is relatively rare with a high preponderance of zeroes. We inspected the ladders of powers (Tukey 1977; Hamilton 1990) to determine an arithmetic transformation resulting in a normal or Gaussian distribution of the truncated count variable. The untransformed variable is characterized by a steep left skew. While none of the common transformations led to a perfectly normally distributed outcome variable, the log transformation yielded the closest transformation as judged by quantile-normal plots as well as a Chi-Square distribution test. The log transformation reduced skewness from 4.0 to 0.36 and kurtosis from 29.49 to 2.21.

[4] Under Dutch penal regime many convicts are allowed (un)accompanied leave during a large part of their sentence. Even those offenders sentenced to a year (or more) in prison can thus be expected to be at risk of offending for some short period. We tried several time periods in the analysis besides one week – days, months – but this did not affect our results.

(Table 1), only information on ages 12-50 was included in the analyses. Further, to reduce the number of person-periods we used three-year periods instead of one-year periods. Collapsing time periods was motivated by the increased data complexity using all 38 time points from age 12 to age 50. As a sensitivity check of the three-year decision, we compared the results to both one-year and two-year groupings. The results were identical for the different grouping decisions and we present the results for the three-year grouping due to a higher stability in the model. The fully constructed data-file contains information for 59,995 person-periods (unweighted) for 4,615 individuals.

<center>* Table 1 about here*</center>

METHODS

Two-Part Latent Growth Model (LGM)

Because our primary interest lies in comparing results for participation and frequency, we sought an approach that provided a reasonable and appropriate strategy. In this study, we employ a Two-Part Latent Growth modeling strategy (Blozis, Feldman, & Conger 2007; Brown et al. 2005; Duan, Manning, Morris, & Newhouse 1983; Manning et al. 1981; Muthén 2001; Olsen & Schafer 2001; Witkiewitz. & Masyn 2008). As a longitudinal adaptation to two-part (or two-equation) multiple regression models (Ellickson et al. 2001; Manning 1997), this strategy decomposes the original distribution of conviction in a 3-year period from age 12 to age 50 into two parts (Figure 1). The two measurement models shown below (Olsen & Schafer 2001:731-732) present this decomposition formally:

<center>15</center>

$$
U_{ij} = \begin{cases} 1 & \text{if } Y_{ij} \neq 0 \\ 0 & \text{if } Y_{ij} = 0 \end{cases}
$$

and

$$
Y_{ij} = \begin{cases} g(Y_{ij}) & \text{if } Y_{ij} \neq 0 \\ \text{irrelevant if } Y_{ij} = 0 \end{cases}
$$

It is assumed that g is a monotone increasing function (e.g., log) that enables an approximation of Y_{ij} by a Gaussian distribution. The responses are estimated by a pair of correlated random effects models, one for the logit probability of $U_{ij}=1$ and one for the mean conditional response for y>0, i.e., $E(Y_{ij} | U_{ij}=1)$.

Figure 1 about here

In Part 1 of the model (the u-part, found in the top portion of Figure 1), no conviction was separated from the rest of the distribution by creation of binary indicator variables distinguishing any positive level of conviction in the time period (coded 1) from non-conviction (coded 0). Conviction-versus-non-conviction outcome variables were analyzed as a random-effects logistic growth model with the log-odds of conviction regressed on growth factors (Muthén 1996). Time of measurement may be included to allow intercepts, slopes etc. to vary by subject (Olson & Schafer 2001:731f).

Part 2 of the model (the y-part) consisted of continuous indicator variables representing the frequency of convictions, given that some conviction had taken place (i.e., excluding zeroes). Here, each frequency-of-conviction outcome was modeled as a Latent Growth Model with growth factors of nonzero conviction regressed on background variables following traditional latent growth modeling (Curran 2000; Duncan & Duncan 1996; Taylor, Graham, Cumsille, & Hansen 2000). The model for the continuous response is:

$$Y_i = X_i^* \gamma + Z_i^* d_i + \varepsilon_i$$

where Y_i is the vector containing all conditional values of Y_{ij} for subject i, given $U_{ij}=1$. The residuals ε_i are distributed as $N(0, \delta^2 I)$; X_i^* and Z_i^* are matrices of covariates. The random coefficients of the u- and the y-part (c_i and d_i respectively) are assumed to be jointly normally distributed and possibly correlated (Olson & Schafer 2001:732):

$$b_i = \begin{pmatrix} c_i \\ d_i \end{pmatrix} \sim N\left(0, \psi = \begin{pmatrix} \psi_{cc} & \psi_{cd} \\ \psi_{dc} & \psi_{dd} \end{pmatrix} \right)$$

It is possible for an individual to have no convictions at any given time period. Thus, individuals who reported no convictions contribute little information to the estimation of γ, δ^2, ψ_{dd} and ψ_{cd}. If $\psi_{cd} = 0$, the two parts of the model are independent. In the context of offending, independence would imply that the probability of conviction at one occasion has no influence on the number of convictions, if any, at other occasions. Only in that situation estimates are unbiased when analyzing the two parts of the model separately.

In sum, the Two-Part model allows different covariates being related to the u-versus the y-part of the model (see also Nagin & Smith's (1990) Zero-Inflated Tobit), estimates the participation and frequency processes by a pair of correlated random coefficients (where an individual with zero convictions at some interval contributes little information to the estimation of Y_i), and as compared to Zero-Inflated count and negative binomial models – zeroes are excluded from the y-part. In other words, the conditional mean of y, given that it is non-zero, is highly meaningful from a substantive point of view. The use of the Two-Part model to analyze longitudinal data explicitly distinguishes between participation and frequency and thus suits our primary interest.

Model Building Results

  The procedure for constructing the Two-Part LGMs consisted of first identifying

the unconditional (i.e., without background variables) functional form of change in

participation. Change in conviction-versus-non-conviction outcomes was modeled as

linear, quadratic, or cubic growth. Loadings for linear, quadratic, and cubic growth

factors were specified as orthogonal polynomial contrasts with intercepts centered at age

24-26 (Raudenbush & Xiao 2001).[5] These different parameterizations were selected in

order to model change in conviction patterns as a constant process (i.e., using linear

growth) or with gradual acceleration or deceleration in conviction (i.e., using quadratic or

cubic growth). Also, we tested if one or more of the growth factors (e.g., intercept, slope

etc.) were random effects. Model fit was assessed by inspecting fit statistics for nested

(i.e., Chi-Square Test) and non-nested (i.e., Bayesian Information Criterion: BIC) model

specifications. While models with increasing numbers of growth factors are compared via

a Chi-Square Test, the BIC was used to test if a growth factor was random. A series of

seven nested models (Model A thru Model G) were estimated, which differed in the

number of growth parameters and the extent to which these were modeled as random or

fixed effects (Table 2). Model F was identified as the best model as judged by the lowest

BIC and significant Chi-Square change. While the intercept to the quadratic slope was

allowed to vary across persons, the cubic slope was modeled as a fixed effect.

  Building upon the best model for participation, we subsequently modeled the

change of frequency in concert with the model for participation. We estimated a series of

five nested models (Model 1 thru Model 5), which differed in the number of growth

---

[5] To ease model convergence by reducing collinearity between growth factors, both processes were
centered at age 24-26.

parameters for the frequency (y-part) and the extent to which these are modeled as random or fixed effects (Table 3). As model parts 1 (u-part) and 2 (y-part) were free to follow different functional forms, it was possible for background variables to have differential effects on growth factors between each model part. To represent the potential conditionality of the frequency-of-conviction outcome on the initial probability of conviction, growth factors between the u-part and y-part were allowed to correlate. Model 5 was identified as the best model, and is characterized by the lowest BIC and a significant Chi-Square change. This model consists of three random growth factors for the conviction probability (u-part) and four random growth factors for the conviction frequency (y-part). The parameter estimates of our preferred model (Model 5) are presented in Table 4. All models were analyzed using Mplus 5.1 (Muthén & Muthén 1998-2008), which provided maximum likelihood parameter estimates with robust standard errors under the assumption of missing at random (MAR) via numerical integration. MAR assumes that missingness depends on observed data, i.e. there are differences between those with observed and missing values, but we observe the ways in which they differ. In the case of the two-part model, individuals with missing on the y-part (frequency) are those who are "0" on the u-part (probability), i.e., they did not engage in offending behavior during a specific 3-year period.

<center>* Tables 2 - 4 about here *</center>

RESULTS

The effects of age

We start by addressing our first and second questions: (1) To what extent and in what way does age have (different?) effects on participation and frequency?, and (2) To

<center>19</center>

what extent is participation and frequency related at the individual level? Recall that Gottfredson and Hirschi deny the need to distinguish participation and frequency, because both reflect underlying propensity. For them the decline in the age-crime curve in early adulthood reflects both decreasing participation and decreasing frequency after the peak. Blumstein et al. instead argue that the participation/frequency dimensions may be differentially related to age and that it is worth investigation. They also hypothesize that participation increases in adolescence, declines in early adulthood, and that there is a decreasing offending participation after the peak, whereas frequency is stable over the lifespan among active offenders or increases for some groups of offenders.

The results of our preferred model (Model 5) shed important light on this distinction. First, the coefficients of age, age^2, and age^3 (Table 4) are significant, indicating a non-linear relationship between age and both participation and frequency. Second, the relationship between age and participation and between age and frequency are rather similar as judged by the linear and nonlinear slopes needed to model this relationship. In Figures 2 and 3, the predicted participation and frequency trajectory are graphically presented based on the estimated coefficients of Model 5 (Table 4).[6] Both figures show the usual increase, peak around age 21-23, and decline thereafter.

* Figures 2 and 3 about here *

Examining the growth parameter variances for participation and frequency reveals significant variation in the mean estimates (Variance=2.527 and 0.322; Std. Error=0.094

---

[6] To obtain age-specific estimates for the probability of conviction, the estimated number of convictions as well as the rate of conviction, it is necessary to integrate over the random effects of the growth factors, obtaining the marginal distribution of the outcomes. This integral is not available in closed, explicit form but has to be obtained via numerical integration. The numerical integration was accomplished using a Monte Carlo simulation approach where we obtained 10,000 random draws from the distribution of the growth factors, using their estimated means, variances, and covariances as obtained from the model output.

and 0.014), indicating significant individual heterogeneity around the mean levels in participation and frequency at age 24-26. Variances for the linear and nonlinear slopes (quadratic for participation and quadratic and cubic for frequency) were also significant, indicating individual heterogeneity in the change of participation and frequency.

The parameter estimates of Model 5 (Table 4) also reveal that there is a clear relationship between the probability of participation and the frequency of conviction. The covariance coefficient for the two intercepts (iu with iy) is 0.858 (Std. Error=0.032), indicating that in years where individuals have a high probability of conviction they also tend to have a high probability of being convicted many times (frequency). Similarly, the linear growth factors were significantly correlated (su with sy: Est=0.274, Std. Error=0.020), indicating that increases in the probability of participation are significantly and substantially related to increases in frequency.

Based on the estimated coefficients of Model 5 (Table 4) the predicted conviction rate in each year can be calculated. Graphically presented in Figure 4, findings correspond well to the aggregate age-crime curve. We now know that this age-conviction curve results both from age-graded differences in participation (more adolescents than adults actively involved in crime) and from age-graded differences in frequency. Importantly, given the high (but not perfect) correlation between the probabilities of participation and – for those who participate – the frequency of their offending, individuals in years with relatively high participation rates will also show elevated conviction rates. This indicates that analyzing conviction rates while ignoring participation probabilities will likely yield biased estimates of λ. Researchers have made a similar observation regarding conviction rates when ignoring individual instances of

incarceration or death (i.e., examples of a zero probability in participation). In short, our

evaluation of the evidence concerning the hypothesis about the similarity of age trends

for participation and frequency offers strong support for Gottfredson and Hirschi's view.

* Figure 4 about here *

The effects of sex and marriage status

The debate between Blumstein et al., Gottfredson and Hirschi, and Sampson and

Laub also concerns whether individual characteristics and life circumstances relate to

criminal activity and whether the impact differs between participation and frequency.

Specifically, Blumstein et al. claim that for participation and frequency, the effects of

individual characteristics may differ, while Gottfredson and Hirschi clearly state that the

causes underlying all criminal career dimensions are the same, regardless of which one is

investigated. They further claim that life events have no effect on criminal careers,

whereas Sampson and Laub argue that life events can be an important correlate of

desistance/persistence but do not specify whether the effect of life events vary across the

participation/frequency dimensions. These hypotheses inspired us to our third question:

(3) To what extent are individual characteristics (sex) and life circumstances (marriage)

related to participation and frequency?[7]

---

[7] Analysis of background variables in conditional models were conducted using two-tailed significance tests ($p < .05$). Gender was modeled to have a time invariant (i.e., regression onto the intercept) and a time-variant (i.e., regression onto the linear and nonlinear growth factors) effect. Marriage status was modeled with a time invariant effect, i.e., its effect was constrained to be constant over time (i.e., Proportional Hazard). The Two-Part LGM has the advantage that different sets of background variables can influence the two parts of the model differently. Importantly, even if the same covariates are used in both parts (as was done in this application), it will generally not be true that $X_i^*=X_i$ and $Z_i^*=Z_i$. And while the impact of the background variables can be compared in terms of its sign and significance, their relative substantive magnitude cannot be compared directly, given the difference in the scales of the u-part (i.e., log odds) versus the y-part (i.e., linear).

We extend our preferred model (Model 5), and include two theoretically important constructs as predictors. Acknowledging the lower crime rate among females, we include sex as a time invariant predictor (Model 5A). Specifically, we test the extent to which the lower crime rate among females is due to a lower probability of conviction as well as a lower frequency of convictions. We also include marital status as a time variant predictor with a time invariant effect (Model 5B). Studies have documented that marriage exerts social control which increases the likelihood of desistance (Blockland, Nagin & Nieuwbeerta, 2005; Laub et al. 1998; Laub and Sampson 2003; Piquero et al. 2002). While the inclusion of these predictors on conviction probability and conviction frequency separately is not new, in the Two-Part model these are allowed to simultaneously influence participation and frequency, and allows for a more fine-grained depiction about the processes underlying changes in participation and frequency.

First, using the unconditional model (Model 5) as a point of departure, we added sex as a predictor of the growth parameters; that is, we allowed sex to have a time invariant (intercept) as well as a structured time variant effect (slope to cubic slope) (Table 4, Model 5A). As judged by the log-likelihood this resulted in an overall better fitting model (Chi-Square Delta=265.206, df=7, p<0.001). Significant sex differences were found with respect to participation and frequency. As expected, the effect for sex on conviction probability was negative, indicating that females at age 24-26 compared to males at the same age were 4.6 times (i.e., 1 / 0.22) less likely to be convicted (Est.=-1.535, Std. Error=0.105, OR=0.22). The effect of sex on conviction frequency was also negative: females at age 24-26 start off being convicted less frequently (Est.=-0.381, Std. Error=0.042) than males. Sex also has a significant impact on the effects of age, age^2, and

age[3], i.e., both on the y-part (see the sy, qy and cy on woman parameters) and the u-part (see the su, qu and cu on woman parameters), indicating that men and women differ in their developmental course of participation and frequency.

Subsequently, we add marital status as a time dependent predictor of growth in the probability of participation and frequency of conviction (Table 4, Model 5B). Given our interest of validating the unconditional model, marital status is modeled in a proportional hazard fashion, i.e., the effect is constrained to be equal across time. As judged by the log-likelihood, this again results in a better fitting model (Chi-Square Delta = 179.018, df=2, p<0.001). The effects of marriage on the probability (U-Part: Est.=-0.476, Std. Error=0.044) and frequency of conviction (Y-Part: Est.=-0.171, Std. Error=0.016) are both negative indicating that individuals in a state of marriage are almost half as likely (i.e., $\exp^{-0.476}$=0.63) of being convicted and – if they are convicted – in a state of marriage they have, on average, .171 less convictions.[8]

Finally, we graph the predicted participation, frequency and conviction rate trajectories for the four groups (sex by marriage status) based on the coefficients of our most extended model (Model 5B, Table 4). We present the predicted trajectories for a hypothetical man and a woman who marry at age 24-26 in Figures 5 through 7.

* Figures 5 - 7 about here *

The figures show clear sex-differences in all three instances (i.e., probability of conviction, frequency of conviction, and rate of conviction). First, higher estimates are found in all instances for males. Second, females tend to show a delayed peak in conviction. While males display the highest probability and frequency of conviction(s) in

---

[8] We view the marriage/crime relationship as another opportunity for comparing relationships to frequency and participation (much like sex), but it should not be viewed as causal. A full treatment of this issue is beyond the scope of this paper (see Laub et al. 1998; King et al. 2007; Bersani et al. 2009).

the early 20s, females peak in their late 20s. Third, starting in the 40s, while the absolute differences across sex appear to become smaller as the trajectories for males and females appear to converge, the ranking of males over females remains stable.

The figures also show clear effects of marrying (i.e., at age 25 as in our hypothetical example). Individuals in a state of marriage have a substantially lower probability of being convicted (Figure 5) and – if they are convicted –they are less frequently convicted while in a state of marriage (Figure 6). This adds up to the fact that individuals in a state of marriage have lower conviction rates (Figure 7). The effect of marriage among males and females regarding participation and frequency is quite similar.

DISCUSSION

Recognizing the small and limited empirical research on the distinction between participation and frequency, we used data on criminal convictions over the lifespan for almost 5,000 persons convicted in the Netherlands along with recently developed Two-Part Growth Models to examine whether there is a meaningful empirical distinction between participation and frequency, as evidenced by their relationships to age, gender, and marriage. In so doing, we used Two-Part Growth models that exhibited several virtues including the ability to: (1) simultaneously estimate parameters of time series for participation and frequency, (2) allow parameters of the participation- and frequency-parts of the model to be correlated, (3) capture unobserved variation in both participation and frequency (accomplished by allowing random variation for coefficients for each

individual, i.e., individual trajectories), and (4) test effects of stable individual characteristics and time-varying life circumstances.[9]

Three specific questions were addressed. First, we examined the relationship between age and both participation and frequency. Results uncovered a non-linear relationship between age and both participation and frequency, and that the relationship between age and participation and between age and frequency were quite similar, but also with significant individual variation around the estimated means. With age, both participation and frequency peaked in early adulthood and declined thereafter.

Second, when we assessed the individual-level relationship between participation and frequency, we found a clear relationship between the probability of participation and the frequency of conviction such that in years where individuals had a relatively high probability of conviction they also had a higher probability of conviction frequency. Further, after we calculated the predicted conviction rate in each year, results were consistent with the aggregate age-crime curve.

Finally, we studied the extent to which individual characteristics (sex) and life circumstances (marriage) related to participation and frequency. Results indicated that: compared to males, females were less likely to be convicted and were less frequently convicted; males and females differed in their developmental course of participation and frequency; and the effects of marriage on the probability and frequency of conviction were both negative indicating that when married, individuals were less likely to be convicted and when convicted, less frequently so.

---

[9] Although we did not do so in this paper, the current model could be extended by adding mixtures to the u and/or the y-part to further explore individual variability, and that, in this model the effects of covariates could not only vary for the two parts, but also in terms of the trajectory membership.

Thus, we find essentially identical relationships of both participation and frequency to age, sex, and marriage, which is consistent with Gottfredson and Hirschi and contrary to the claim that participation but not frequency varies with age. Our results square away with Gottfredson and Hirschi, who argue that such a pattern of findings would emerge from there being only causes of a crime as a whole, not separate causes of different criminal career dimensions. Their hypothesis appears to receive support in the CCLS primarily because participation and frequency are closely linked and vary with age. Criminal careerists advocating the distinction between the participation and frequency dimensions are likely to have a difficult time reconciling these findings.

Results also resonate well with Sampson and Laub's (1993) theory and Laub and Sampson's (2003) recent long-term follow-up findings concerning the effects of life events, such as marriage. Where Gottfredson and Hirschi hypothesize that life circumstances have no effects on participation and frequency, Sampson and Laub's research, as well as findings from the current study contradict the purely static hypothesis and provide evidence for a more general but dynamic theory of crime.

With these theoretical implications in hand—and taken in concert with prior studies on the participation/frequency distinction—our results offer a more complete (yet still imperfect) characterization of how participation and frequency vary over the life course. Our findings are especially useful because unlike prior studies which were limited to a brief snapshot of the juvenile years among normative/community samples, our effort tracked criminal offending among a large sample of offenders followed well into adulthood that allowed us to portray and investigate criminal careers in a more

demonstrative manner. These advantages are a certain improvement over previous efforts and represent a baseline for which other longitudinal investigations should be compared.

Of course, ours is not the final word on this issue. First, although there were certain features of the CCLS that improve upon extant research (long term follow-up period, non-US, inclusion of street time and death information), they contain data on official records among a predominantly all-white male sample from the 1980's. Replication of our findings and extension to other and more recent data sources is important. Second, we did not parcel out violent crimes. Given the strong correlation between frequency and violence (violent offenses are more common among frequent offenders), it would be interesting to examine the participation/frequency distinction with a focus on violence. Third, we only examined one particular life event, marriage, and others are worthy of a deeper understanding of how life events alter situations and opportunities. In short, data remain thin and theory mixed with respect to the causal process underlying the relationship between participation and frequency. Recent studies have not given much attention to this issue, and it remains unclear whether the factors that are related to participation and frequency are similarly related to the factors that are related to desistance from crime (Loeber et al. 2008).

REFERENCES

Barnett, A., Blumstein, A., & Farrington, D.P. 1989. A prospective test of a criminal career model. *Criminology* 27:373-388.

Bersani, Bianca, John H. Laub, and Paul Nieuwbeerta. 2009. Marriage and Desistance from Crime in the Netherlands: Do Gender and Socio-Historical Context Matter? *Journal of Quantitative Criminology* 25:3-24.

Blokland, Arjan A.J. and Paul Nieuwbeerta. 2005. The Effects of Life Circumstances on Longitudinal Trajectories of Offending. *Criminology* 43:1203-1240.

Blokland, A. A.J., Nagin, D.S. & Nieuwbeerta, P. 2005. Life span offending trajectories of a Dutch conviction cohort. *Criminology* 43(4) 919-954.

Blozis, S.A., Feldman, B. & Conger, R.D. 2007. Adolescent alcohol use and adult alcohol disorders: A two-part random-effects model with diagnostic outcomes. *Drug and Alcohol Dependence, 88, S85-S96.*

Blumstein, A., Cohen, J., Roth, J.A. & Visher, C.A. 1986. *Criminal Careers and Career Criminals Volume 1*. Washington, D.C.: National Academy Press.

Blumstein, A., Cohen, J., & Farrington, D.P. 1988a. Criminal career research: Its value for criminology. *Criminology* 26:1-35.

Blumstein, A., Cohen, J., & Farrington, D.P. 1988b. Longitudinal and criminal career research: Further clarifications." *Criminology* 26:57-74.

Blumstein, A., & Graddy, E. 1982. Prevalence and recidivism in index arrests: A feedback model. *Law and Society Review* 16:265-290.

Blumstein, A. 2005. An overview of the symposium and some next steps. *Annals of the American Academy of Political and Social Science* 602:242–258

Brown, E.C., Catalano, C.B., Fleming, C.B., Haggerty, K.P. & Abbot, R.D. 2005. Adolescent substance use outcomes in the Raising Healthy Children Project: A two-part latent growth curve analysis. *Journal of Consulting and Clinical Psychology* 73:699-710.

Curran, P. J. 2000. A latent curve framework for the study of developmental trajectories in adolescent substance use. In J. S. Rose, L. Chassin, C. C. Presson, & S. J. Sherman (Eds.), *Multivariate applications in substance use research: New methods for new questions* (pp. 1-42). Mahwah, NJ: Erlbaum.

Duan, N., Manning, W.G., Morris, C.N., & Newhouse, J.P. (1983). A comparison of alternative models for the demand for medical care. *Journal of Business and Economic Statistics, 1,* 115-126.

Duncan, S. C., & Duncan, T.E. 1996. A multivariate latent growth curve analysis of adolescent substance use. *Structural Equation Modeling 3:*323-347.

Farrington, D.P. 1986. Age and crime. In M. Tonry and N. Morris (eds.), *Crime and Justice: An Annual Review*. Chicago: University of Chicago Press.

Farrington, D.P. 2003. Developmental and life-course criminology: Key theoretical and empirical issues—the 2002 Sutherland Award Address. *Criminology* 41:221-255.

Ellickson, P. L., Tucker, J. S., Klein, D. J., & McGuigan, K. A. 2001. Prospective risk factors for alcohol misuse in late adolescence. *Journal of Studies on Alcohol 62:* 773-782.

Greenberg, D.F. 1991. Modeling criminal careers. *Criminology, 1*, 17-45.

Glueck, S. & Glueck, E. 1950 *Unraveling Juvenile Delinquency*. New York: Commonwealth Fund.

Gottfredson, M.R. 2005. Offender classifications and treatment effects in developmental criminology:. A propensity/event consideration. *Annals of the. American Academy of Political and Social Science* 602:46-56.

Gottfredson, Michael R. and Travis Hirschi.1986. The True Value of Lambda Would Appear to Be Zero. *Criminology* 24:213-234.

Gottfredson, Michael R. and Travis Hirschi. 1988. Science, Public Policy, and the Career Paradigm. *Criminology* 26:37-55.

Greenberg, David F. 1991. Modeling Criminal Careers. *Criminology* 25:17-46.

Hamilton, L.C. 1990. *Statistics with STATA*. Pacific Grove, CA: Brooks/Cole.

Hirschi, T.,& Gottfredson, M.R., 1995. Control theory and the life-course perspective. *Studies on Crime and Crime Prevention*, *4*(2), 131-142.

King, R., Massoglia, M., & MacMillan, R. 2007. The context of marriage and crime: Gender, the propensity to marry, and offending in early adulthood. *Criminology,* 45:33-65.

Kreuter, F. & Muthen, B. 2008. Analyzing criminal trajectory profiles: bridging multi-level and group-based approaches using growth mixture modeling. *Journal of Quantitative Criminology 24:1-31.*

Lambert, D. (1992). Zero-inflated Poisson regression, with an application to defects in manufacturing. *Technometrics, 34*, 1-14.

Land, Kenneth C. 1992. Models of Criminal Careers: Some Suggestions for Moving Beyond the Current Debate. *Criminology* 30:149-155.

Laub, J. H. &. Sampson, R.J. 2003. *Shared Beginnings, Divergent Lives. Delinquent Boys to Age 70.* Cambridge, MA: Harvard University Press.

Laub, John H., Daniel S. Nagin, and Robert J. Sampson. 1998. Good Marriages and Trajectories of Change in Criminal Offending. American Sociological Review 63:225-238.

Little, Rod J.A. and D.B. Rubin. 1987. *Statistical Analysis with Missing Data.* New York: John Wiley.

Loeber, R., Farrington, D.P., Stouthamer-Loeber, M., & White, H.R. 2008. *Violence and Serious Theft: Development and Prediction from Childhood to Adulthood*. New York, NY: Routledge.

Manning, W. 1997. Alternative econometric models of alcohol demand. In K. J. Bryant & M.Windle (Eds.), *The science of prevention: Methodological advances from alcohol and substance abuse research* (pp. 101-121). Washington, DC: American Psychological Association.

Manning, W., Morris, C.N., Newhouse, J.P., Orr, L.L., Duan, N., Keeler, E.B., Leibowitz, A., Marquis, K.H., Marquis, M.S., & Phelps, C.E. (1981). A two-part model of the demand for medical care: Preliminary results from the health insurance experiment. In J. van der Gaag & M. Perlman (Eds.). *Health, Economics and Health Economics* (pp. 103-104). Amsterdam: North-Holland.

Moffitt, T.E, Caspi, A., Rutter, M. & Silva, P.A., 2001. *Sex Differences in Antisocial Behaviour: Conduct Disorder, Delinquency, and Violence in the Dunedin Longitudinal Study*, Cambridge University Press: Cambridge, UK.

Muthen, B.O. 1996. Growth modeling with binary responses. In: A.V. Eye & C. Clogg (Eds.), *Categorical Variables in Developmental Research: Methods of Analysis*

Muthén, L.K., & Muthén, B.O. 1998-2008. *Mplus User's Guide* (Version 5.1.). Los Angeles, CA: Muthén & Muthén.

Muthén, B., & Asparouhov, T. (2002, December 9). Latent variable analysis with categorical outcomes: Multiple-group and growth modeling in Mplus. *Mplus Web Notes: No. 4, Version 5*. Retrieved January 27, 2004, from the World Wide Web: http://www.statmodel.com/mplus/examples/webnote.html.

Muthén, B.O. 2001. *Two-part growth mixture modeling*. Unpublished manuscript.

Muthén, B., 2004. Latent variable analysis: Growth mixture modeling and related

techniques for longitudinal data. In: Kaplan, D. (Ed.), *Handbook of Quantitative Methodology for the Social Sciences*. Sage, Newbury Park, CA. pp. 345-368.

Muthen, B., & Shedden, K. 1999. Finite mixture modeling with mixture outcomes using the EM algorithm. *Biometrics* 6:463-469.

Nagin, D.S., & Smith, D.A. 1990. Participation in and frequency of delinquent behavior: A test for structural difference. *Journal of Quantitative Criminology* 6: 335-356.

Nagin, D.S. 2005. *Group-Based Modeling of Development Over the Life Course*. Cambridge, MA: Harvard University Press.

Nieuwbeerta, P. and Blokland, A.A.J. 2003. *Criminal Careers of Adult Dutch Offenders (Codebook and Documentation).* Leiden: NSCR.

Nieuwbeerta, P. & Piquero, A.R. 2008. Mortality rates and causes of death of convicted Dutch criminals 25 years later. *Journal of Research in Crime and Delinquency 45: 256-286*.

Olsen, M.K., & Schafer, J.L. 2001. A two-part random-effects model for semicontinuous longitudinal data. *Journal of the American Statistical Association 96,* 730-745.

Osgood, D.W. 2000. Poisson based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology, 1*, 21-42.

Osgood, D.W. 2005. Making sense of crime and the life course. *Annals* 602:196-211.

Osgood, D.W. and D.C. Rowe. 1994. Bridging criminal careers, theory, and policy through latent variable models of individual offending. *Criminology* 32:517-554.

Osgood, D.W., Finken, L.L., & McMorris, B.J. 2002. Analyzing Multiple-item Measures of Crime and Deviance II: Tobit Regression Analysis of Transformed Scores. *Journal of Quantitative Criminology* 18:319-347.

Paternoster, R. & Triplett, R. 1988. Disaggregating self-reported delinquency and its implications for theory. *Criminology* 26:591-625.

Paternoster, Raymond, Charles Dean, Alex Piquero, Paul Mazerolle, and Robert Brame. 1997. Generality, Continuity and Change in Offending Careers. *Journal of Quantitative Criminology* 13:231-266.

Piquero, Alex R., Alfred Blumstein, Robert Brame, Rudy Haapanen, Edward P. Mulvey, and Daniel S. Nagin. 2001. Assessing the Impact of Exposure Time and Incapacitation on Longitudinal Trajectories of Criminal Offending. *Journal of Adolescent Research* 16:54-74.

Piquero, Alex R. Robert Brame, Paul Mazerolle, and Rudy Haapanen. 2002. Crime in Emerging Adulthood. *Criminology* 40:137-169.

Piquero, A.R., Farrington, D.P. & Blumstein, A. 2003. The criminal career paradigm. *Crime and Justice: A Review of Research* 30: 359-506.

Piquero, A.R., Farrington, D.P. & Blumstein, A. 2007. *Key Issues in Criminal Career Research: New Analyses from the Cambridge Study in Delinquent Development*. Cambridge: Cambridge University Press.

Piquero, A.R., Moffitt, T.E., & Wright, B.E. 2007. Self-control and criminal career dimensions. *Journal of Contemporary Criminal Justice* 23:72-89.

Piquero, A.R. 2008. Taking stock of developmental trajectories of criminal activity over the life course." In A. Liberman (Ed.), *The Long View of Crime: A Synthesis of Longitudinal Research*. New York: Springer.

Raudenbush, S.W., & Xiao-Feng, L. 2001. Effects of study duration, frequency of observation, and sample size on power in studies of group differences in polynomial change. *Psychological Methods 6:*387-401.

Rowe, David C., D. Wayne Osgood, and Alan W. Nicewander. 1990. A Latent Trait Approach to Unifying Criminal Careers. *Criminology* 28:237-270.

Sampson, R.J.,& Laub, J.H., 1993. *Crime in the Making: Pathways and Turning Points through Life*. Cambridge, MA: Harvard University Press.

---------2003. Life-course desisters? Trajectories of crime among delinquent boys followed to age 70. *Criminology* 41: 555–592.

---------2005. When prediction fails: From crime-prone boys to heterogeneity in adulthood**.** *Annals of the American Academy of Political and Social Science* 602:73-79.

Shaw, C. 1930. *The Jack-Roller: A Delinquent Boy's Own Story*. Chicago: University of Chicago Press.

Smith, D.A., Visher, C.A., & Jarjoura, G.R. 1991. Dimensions of delinquency*:* Exploring the correlates of participation, frequency, and persistence of delinquent behavior. *Journal of Research in Crime and Delinquency* 28:6-32.

Smith, D.A., & Brame, R. 1994. On the initiation and continuation of delinquency. *Criminology* 32:607-629.

Smith, D.A., & Brame, R. 2003. Tobit models in social science research – Some limitations and a more general alternative. *Sociological Methods and Research, 3*, 364-388.

Sutherland, E. 1939. *Principles of Criminology*. Philadelphia: Lipincott.

Taylor, B. J., Graham, J. W., Cumsille, P., & Hansen, W. B. 2000. Modeling prevention program effects on growth in substance use: Analysis of five years of data from the Adolescent Alcohol Prevention Trial. *Prevention Science 1:*183-197.

Tukey, J.W. 1977. *Exploratory Data Analysis.* Reading, MA: Addison-Wesley.

Vermunt, J.K. 2003. Multilevel latent class models. *Sociological Methodology* 33:213-239.

Witkiewitz, K. & Masyn, K. 2008. Drinking trajectories following an initial lapse. *Psychology of Addictive Behaviors* 22:157-167.

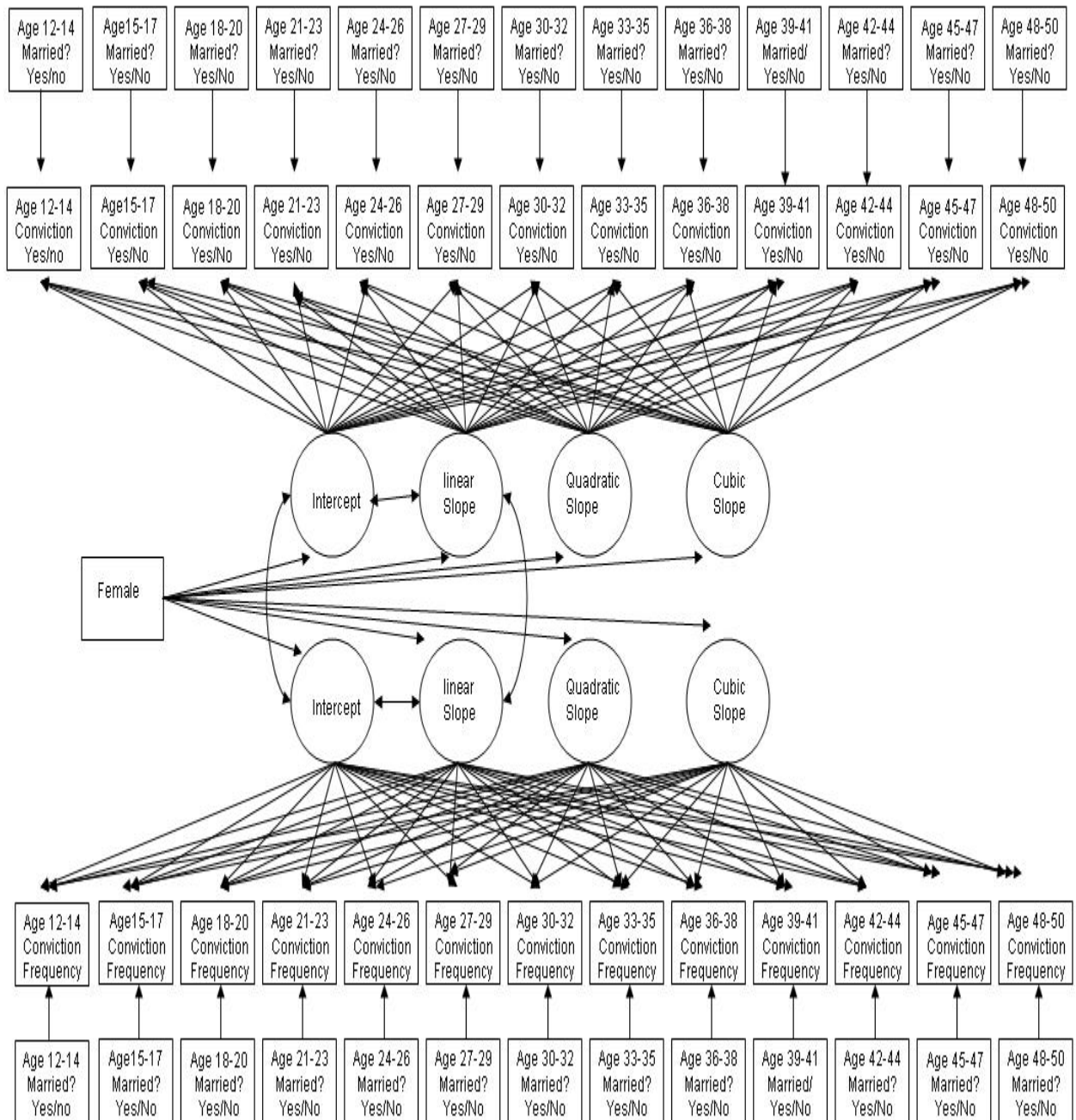**Figure 1: A Twopart Model of Participation and Frequency of Offending**

Table 1. Number of Individuals Observed at Different Ages

Age	Unweighted	Weighted
12	4615	4615
22	4605	4600
32	4547	4561
42	4255	4297
52	2042	2342
62	788	979
72	245	306

Table 2: Comparison of Model fit for Conviction Probability (u-part)

Model	Setting*	LogLikelihood (LL)	# of par	BIC
Model A	Intercept	-28834	2	57684.1
Model B	Intercept + Linear Slope (fixed)	-28618	3	57262.3
Model C	Intercept + Linear Slope	-28424	5	56890.9
Model D	Intercept + Linear Slope + Quadratic Slope (fixed)	-27260	6	54570.2
Model E	Intercept + Linear Slope + Quadratic Slope	-27019	9	54113.3
Model F	Intercept + Linear Slope + Quadratic Slope + Cubic Slope (fixed)	-26672	10	53427.7
Model G	Intercept + Linear Slope + Quadratic Slope + Cubic Slope	-26843	9**	53761.7

* All Coefficients have variance terms – except when mentioned (fixed)
** Only one extra parameter should be estimated in Model G compared to Model F, i.e. variance of the cubic trend. However, the model became very unstable and the covariation of the intercept with the quadratic and cubic trend as well as the covariation of the slope with the quadratic and cubic trend were constrained to zero.

Table 3: Model fit of the Simultaneous Modeling of the Conviction Probability (u-part) and Conviction Frequency (y-part)

	Setting*		Model Fit	
	Model U-Part (see Table 2)	Model Y-part	LL	BIC
Model 1	Model F	Intercept, Linear Slope	-41379.556 (33)	83037.535
Model 2	Model F	Intercept, Linear Slope, Quadratic slope (fixed)	-41191.326 (33)	82661.076
Model 3	Model F	Intercept, Linear Slope, Quadratic Slope	-41061.703 (39)	82452.452
Model 4	Model F	Intercept, Linear Slope, Quadratic Slope, Cubic Slope (fixed)	-40960.086 (41)	82266.092
Model 5	Model F	Intercept, Linear Slope, Quadratic Slope, Cubic Slope	-40873.043 (45)	82125.754

* All Coefficients have variance terms – except when mentioned: (fixed)

Table 4: Parameter Estimates[***] and Model Fit for the unconditional (Model 5) and the Conditional Models (Model 5A and 5B)

	Model 5		Model 5A		Model 5B	
	Parameter		**Parameter**		**Parameter**	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Participation (U-Part)						
Intercept (iu)**	0	fixed	0	fixed	0	fixed
Slope (su)	-0.263	0.033	-0.319	0.034	-0.146	0.037
Quadratic Slope (qu)	-1.293	0.030	-1.304	0.031	-1.340	0.031
Cubic Slope (cu)	0.412	0.015	0.419	0.015	0.413	0.016
iu on woman	na	na	-1.535	0.105	-1.418	0.105
su on woman	na	na	0.731	0.122	0.725	0.122
Qu on woman	na	na	0.213	0.111	0.147	0.111
Cu on woman	na	na	-0.136	0.056	-0.109	0.056
Part on Marriage	na	na	na	na	-0.476	0.044
Frequency (Y-Part)						
Intercept (iy)	0.371	0.012	0.409	0.012	0.480	0.014
Slope (sy)	-0.148	0.015	-0.150	0.015	-0.083	0.016
Quadratic Slope (qy)	-0.164	0.019	-0.194	0.017	-0.208	0.017
Cubic Slope (cy)	0.076	0.011	0.089	0.010	0.085	0.010
iy on woman	na	na	-0.381	0.042	-0.336	0.041
sy on woman	na	na	0.134	0.039	0.131	0.039
Qy on woman	na	na	0.134	0.050	0.114	0.050
Cy on woman	na	na	-0.073	0.021	-0.065	0.021
Lambda on Marriage	na	na	na	na	-0.171	0.016
	(Residual) Variances		**(Residual) Variances**		**(Residual) Variances**	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Participation (U-Part)						
Intercept (iu)	2.527	0.094	2.378	0.090	2.343	0.089
Slope (su)	1.087	0.067	1.055	0.066	1.071	0.067
Quadratic Slope (qu)	0.104	0.017	0.105	0.017	0.107	0.017
Cubic Slope (cu)	fixed	na	fixed	na	fixed	na
Frequency (Y-Part)						
Intercept (iy)	0.322	0.014	0.311	0.014	0.302	0.013
Slope (sy)	0.094	0.010	0.095	0.010	0.094	0.010
Quadratic Slope (qy)	0.060	0.010	0.056	0.009	0.055	0.009
Cubic Slope (cy)	0.009	0.002	0.009	0.002	0.008	0.002
	Covariance*		**Covariance***		**Covariance[*]**	
Iu with su	0.187	0.033	0.214	0.032	0.198	0.032
Iu with iy	0.858	0.032	0.816	0.031	0.799	0.031
Su with sy	0.274	0.020	0.272	0.020	0.272	0.021
Iy with sy	0.037	0.007	0.036	0.007	0.031	0.007
LL (df)	-40873.043 (45)		-40740.440 (52)		-40650.931 (54)	

* For all three models 17 covariances were estimated. ** The growth process of participation and frequency were centered at age 24-26 to ease model convergence. ***All parameter estimates are significant on at least the .05 level.

na : not applicable

Figure 2: Predicted probability of conviction (u-part, Model 5)
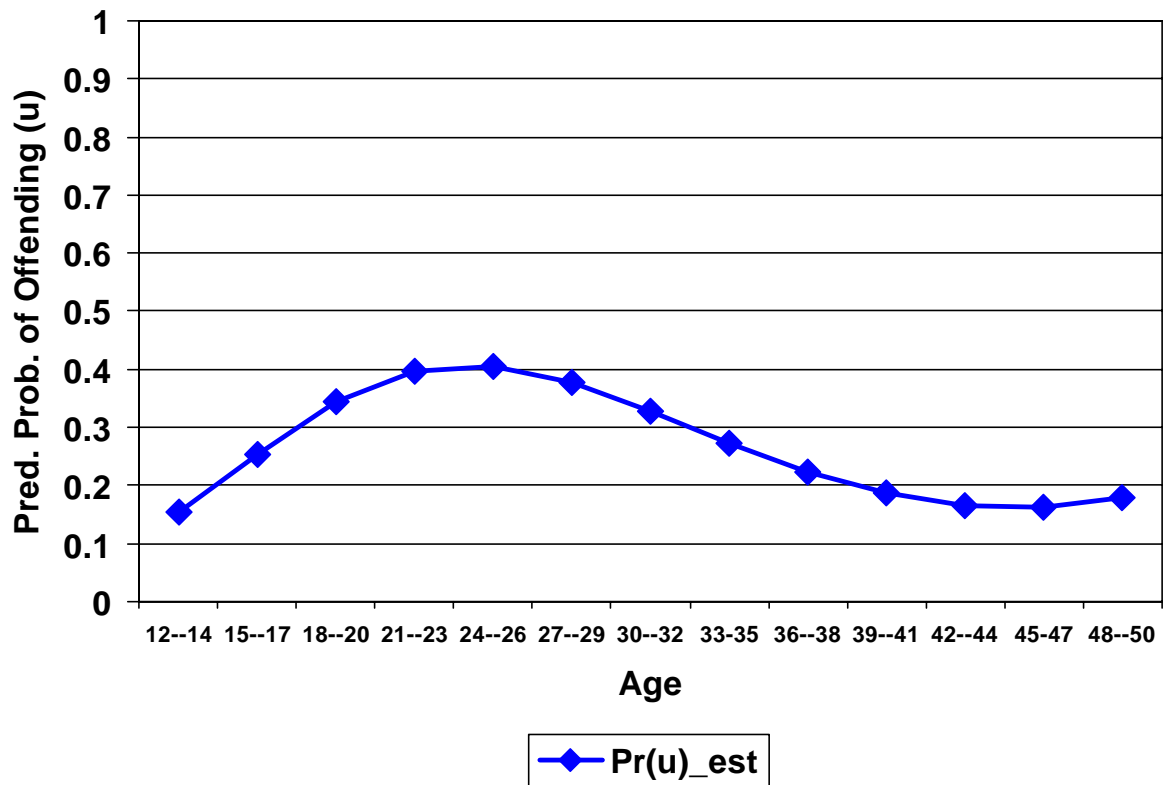
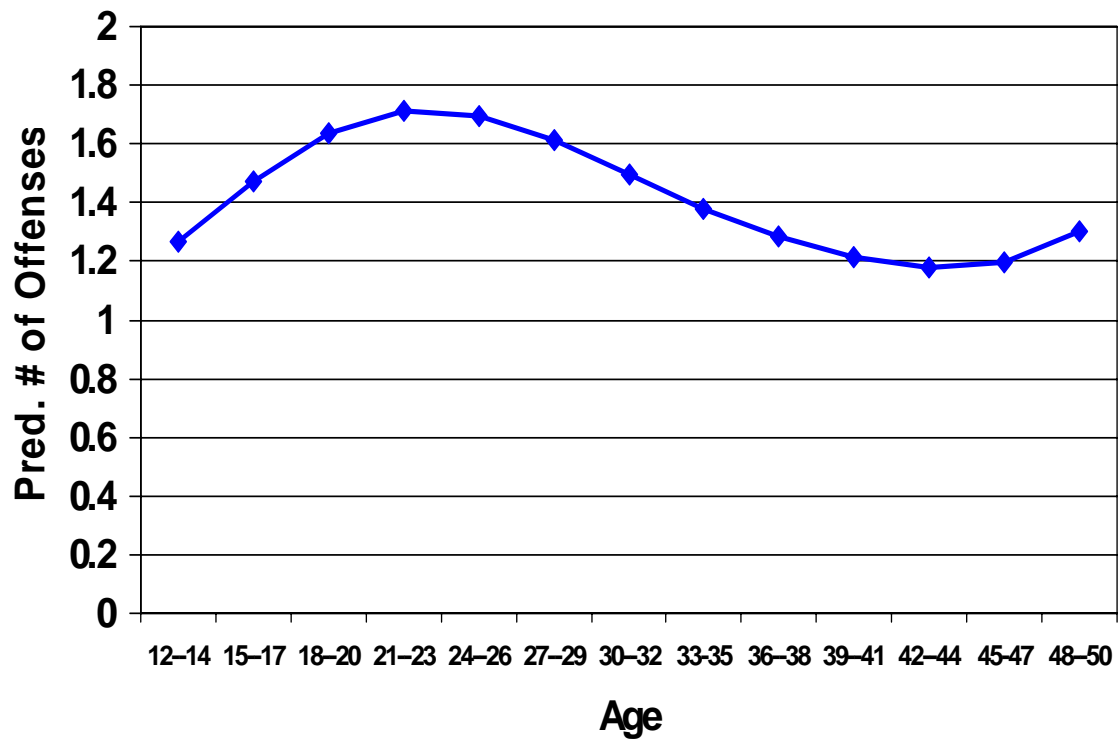**Figure 3: Predicted frequency of conviction (y-part, Model 5)**

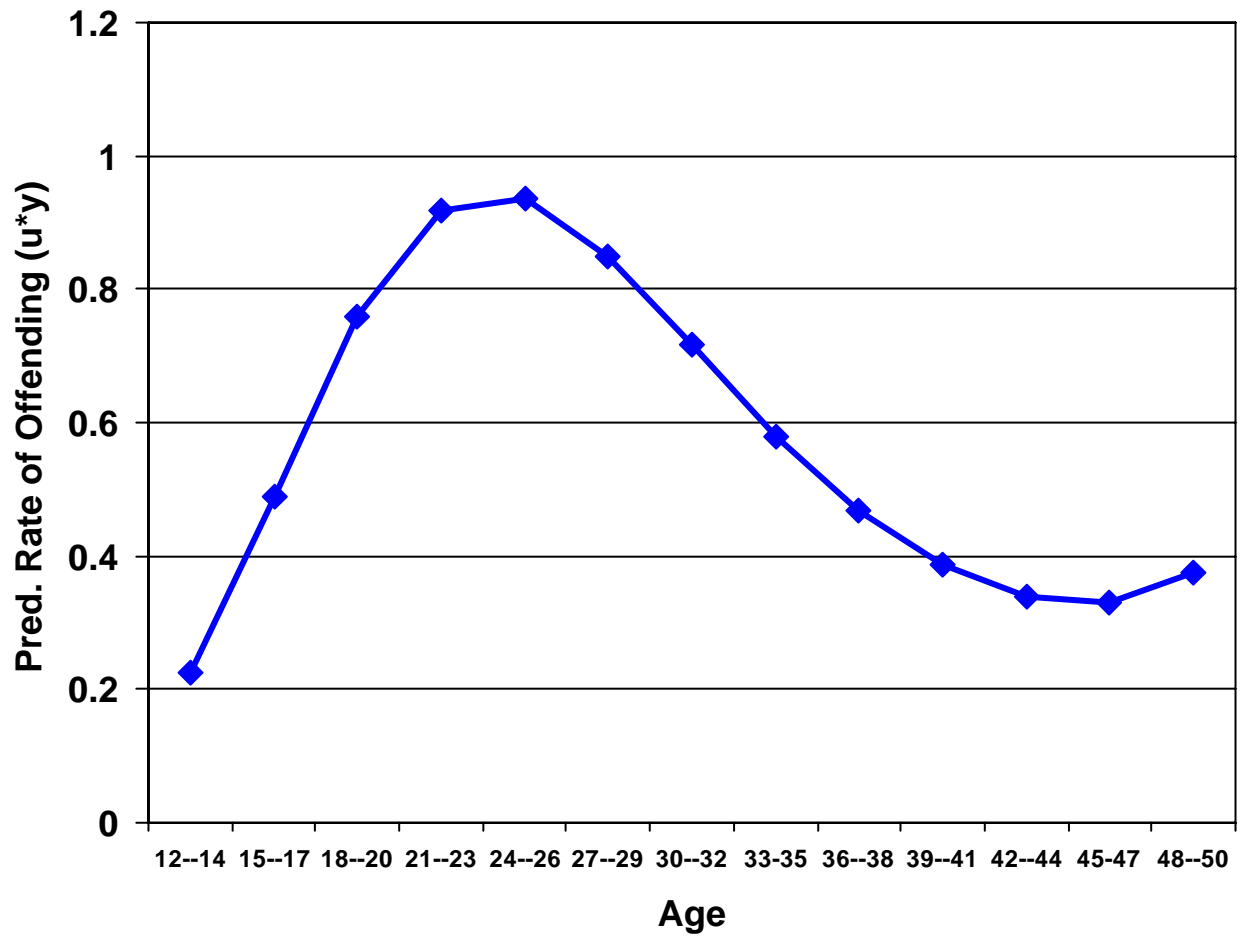**Figure 4: Predicted conviction rate (rate = u*y, Model 5)**

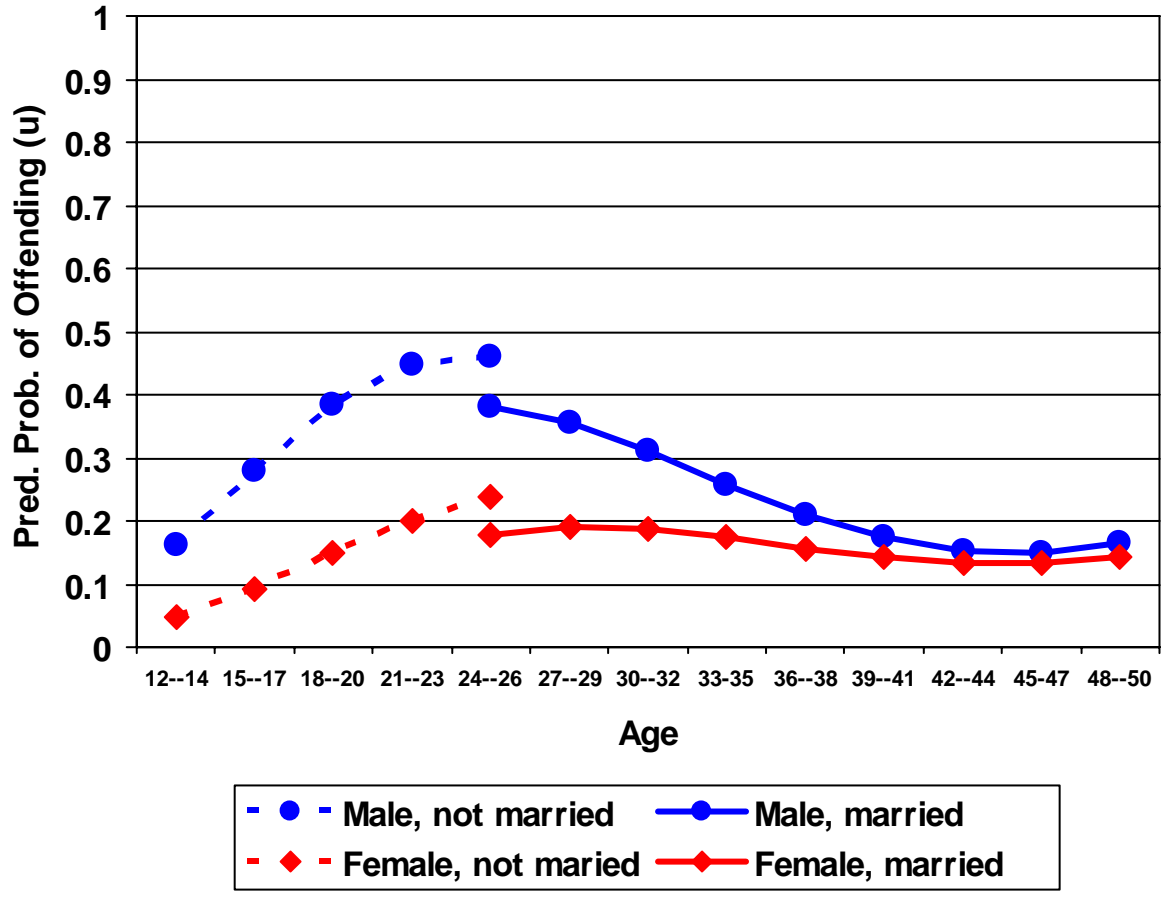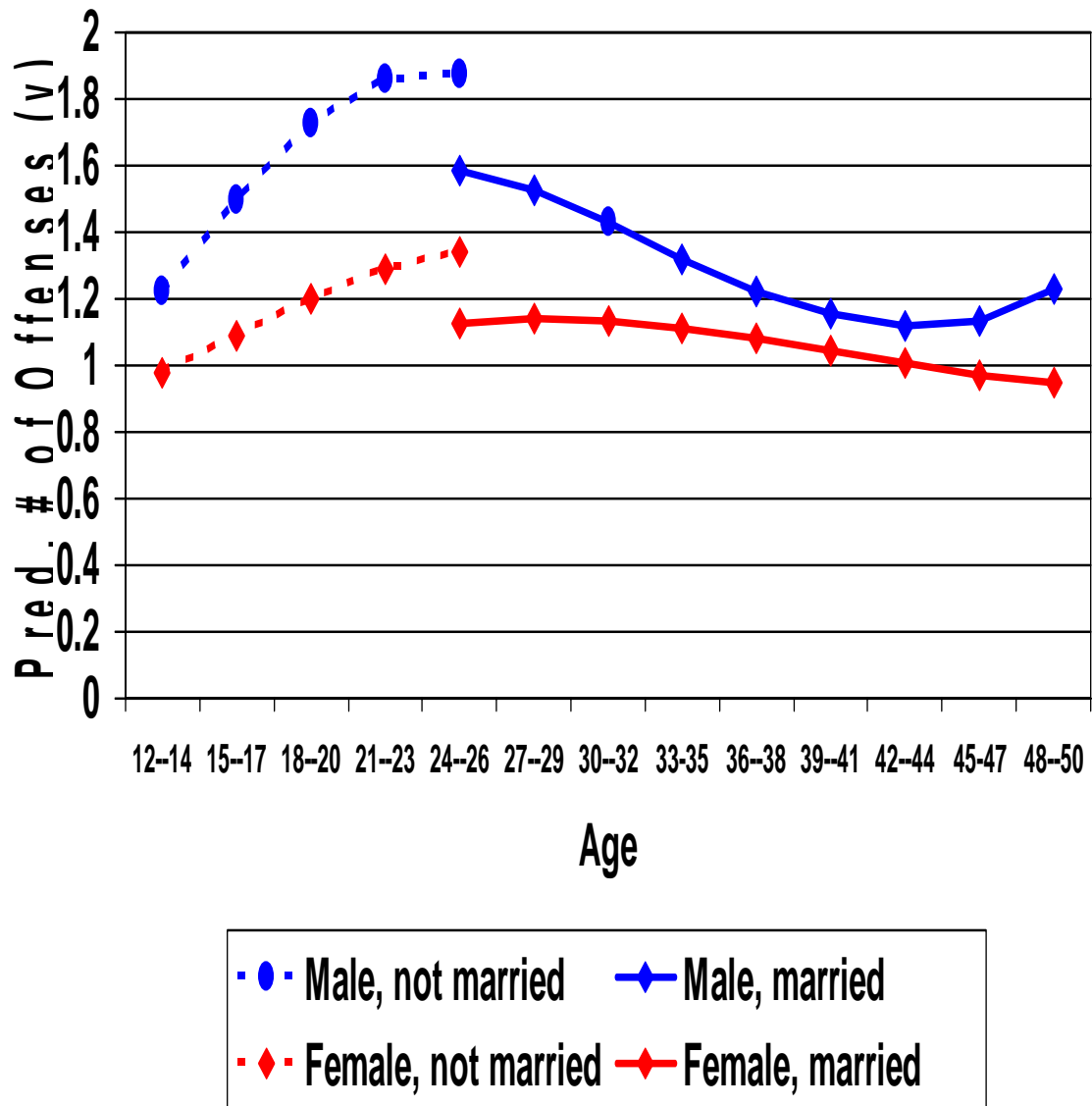**Figure 5: Predicted probability of conviction by gender and change in marriage status at age 25 (u-part, Model 5B)**
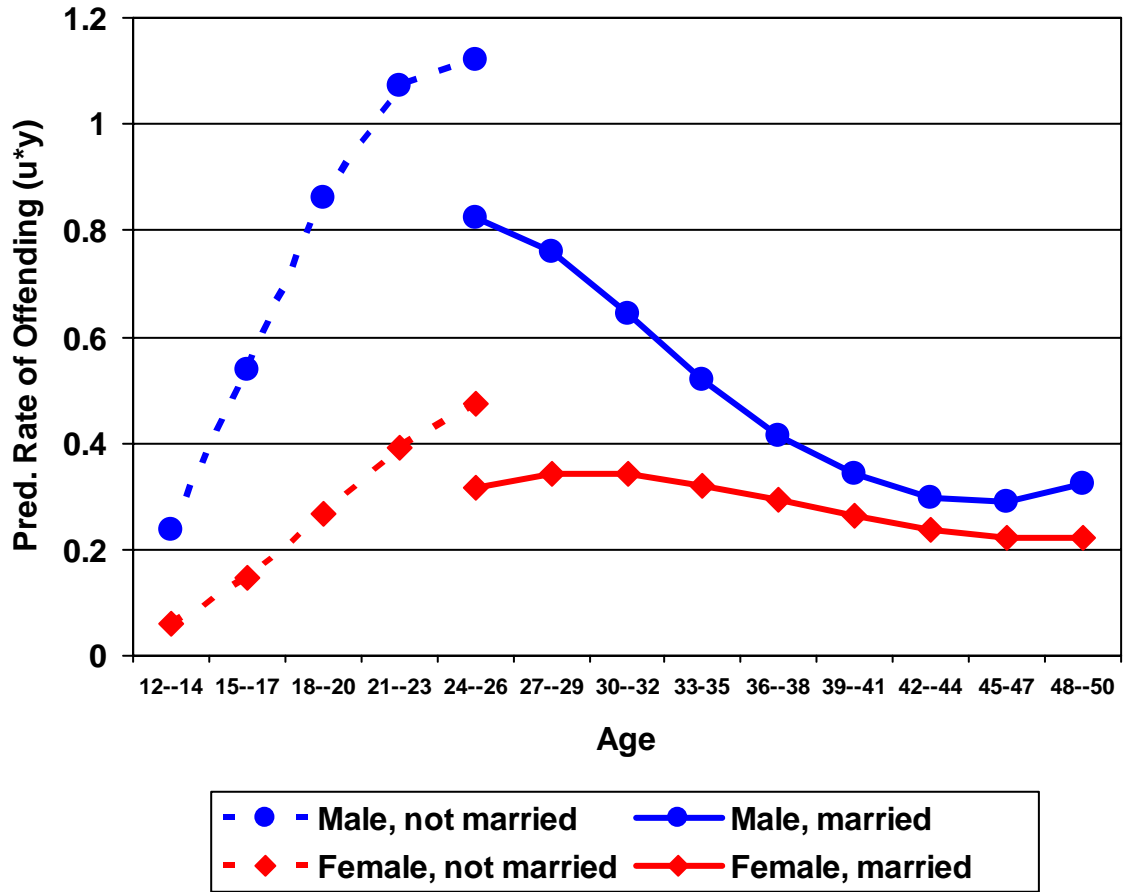
Figure 6: Predicted frequency of conviction by gender and change in marriage status at age 25 (y-part, Model 5B).[10]

---

[10] The predicted number of offenses among non-married females at age 12-14 appears to be smaller than 1, which is due to rounding error.

Figure 7: Predicted conviction rate by gender and change in marriage status at age 25 (rate = u*y, Model 5B)

Author Biographies

Hanno Petras is Assistant Professor in the Department of Criminology & Criminal Justice at the University of Maryland College Park, adjunct Assistant Professor in the Department of Mental Health at Johns Hopkins University and Faculty Associate at the Maryland Population Research Center. His research interests include the development of aggressive behavior, life course criminology, and quantitative research methods.

Paul Nieuwbeerta was senior-researcher at the Netherlands Institute for the Study of Crime and Law Enforcement (NSCR) at the time of writing this paper. Since July 2009, he is Professor in the Department of Criminology at Leiden University in the Netherlands. His research interests include the criminal behavior over the life course, homicide, and the determinants and consequences of sentencing (especially imprisonment).

Alex R. Piquero is Professor in the Department of Criminology & Criminal Justice at the University of Maryland College Park, Executive Counselor of the American Society of Criminology, and Co-Editor of the Journal of Quantitative Criminology. His research interests include criminal careers, criminological theory, and quantitative research methods. He is also the recipient of several research, teaching, and service awards.