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What is This?
Criminal Offending Frequency and Offense Switching

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A basic function of criminal career research is to describe patterns of criminal offending. During the history of the criminal career framework, researchers have divided the conceptual terrain of criminal offending into different dimensions. Two such dimensions include offending frequency and offense switching. Although research on both of these dimensions is extensive, there has been little investigation of their relationship to each other. In this article, the authors use juvenile police contact data from the 1945 Philadelphia birth cohort study to address this issue. In so doing, they extend an existing analytical framework that will allow them to examine the joint distribution of these two variables. Two specific models are compared. The first model hypothesizes that the probability of switching between two categories of offenses (serious violent and all other offenses) will vary with individual offense frequency. The second model hypothesizes that the probability of offense switching and offending frequency are independent of each other. Our analysis suggests that the process implicated by the second model is more consistent with the data.

Keywords: offense frequency; specialization; mixture models

Research on criminal careers has significantly advanced knowledge about several different aspects or dimensions of criminal behavior. Two such dimensions are the frequency or volume of crime committed by individual offenders and the versatility or tendency to switch between different types of criminal activity.

There is a long history in criminology devoted to the estimation of crime frequencies and offending rates for geographic units. For example, the estimation and interpretation of community-level crime frequencies occupied a
substantial part of the Chicago School’s attention (Shaw, 1929; Shaw & McKay, 1972). It is only within the past few decades, however, that empirical research has focused on carefully measuring individual offending rates. The criminal career perspective has placed great emphasis on the measurement of individual offending frequencies, and researchers within that tradition have focused a great deal of attention on measuring the rate of individual offending or \( \lambda \), defined as the number of crimes committed per active offender during some well-defined time period (Blumstein, Cohen, Roth, & Visher, 1986). Thus defined, the individual rate of offending has been the subject of a great deal of subsequent empirical research concerned with the measurement of \( \lambda \), with official and self-report data, the demographic correlates of \( \lambda \), the causal factors that create variation in \( \lambda \), the over-time variation in \( \lambda \), and the public policy implications of these findings (Cohen, 1986). Although this discussion has been quite controversial (see, for example, Gottfredson & Hirschi, 1990), individual offending frequency has become an important part of the research agenda in the field of criminology.

Another dimension of criminal offending of interest here is the extent to which offenders switch between different offending categories or “settle down” into a single offense category. Traditionally, offenders who tend to repeat the same or similar crimes over time have been referred to as offending “specialists,” whereas those whose offending pattern involves a mixture of different types of offenses have been termed “generalists” (Blumstein et al., 1986). Interest in the tendency for offenders to specialize or exhibit versatility in their offending is also of historical importance. In their depiction of the life histories of delinquents they studied, Shaw and his colleagues (1930, 1931) noted that juvenile offenders seemed to participate in a wide variety of offense types.1 As with the frequency of offending, however, it has only been recently that criminologists have focused on the theoretical, public policy, and methodological issues that pertain to offense switching (Blumstein et al., 1986; Farrington, Snyder, & Finnegan, 1988; Wolfgang, Figlio, & Sellin, 1972).

While offense frequency and offense switching are both important topics in their own right, our main interest in this article is on their convergence. Criminal career researchers and developmental criminologists would both make the prediction that the rate of offending and offense switching are related. In addition, we think that the presence or absence of any correlation between these two dimensions of criminal offending has implications for theory. Our purpose in this article, therefore, is to directly examine the joint distribution of offense frequency and offense switching. We do so with an analytical framework that offers a direct test of the hypothesis that high-frequency offenders are more inclined to switch between violent and nonviolent offending than low-frequency offenders.
Using official records of police contacts for juvenile activity from the 1945 Philadelphia birth cohort study (Tracy, Wolfgang, & Figlio, 1990; Wolfgang et al., 1972), we will estimate two different models of the relationship between individual offending rates and the prevalence of offense switching. Our first model allows for the possibility that the probability of offense switching will vary in important ways with individual offending frequency, whereas our second model anticipates no difference in the likelihood of offense switching for different offending-frequency groups. If frequent offenders are more likely to switch crime types than less frequent offenders, we should find greater empirical support for the first model. On the other hand, if there is no relationship between the two, then we should find greater empirical support for the second model.

**OFFENSE FREQUENCY AND SWITCHING**

Researchers in the criminal career tradition have conducted numerous studies of the rate or frequency of criminal offending and how it varies by demographic characteristics and other dimensions of criminal offending such as the timing of onset and the duration of criminal careers (Blumstein et al., 1986; Leblanc & Loeber, 1998; Loeber & LeBlanc, 1990). There is also an extensive literature dating back to the work of Shaw and McKay that investigates the issue of offense specialization. Those who have studied this issue by examining offense-switching patterns by offenders over time often find significant versatility in offending accompanied by a modest tendency for offenders to repeat the same kind or general type of offense (Blumstein, Cohen, Das, & Moitra, 1988; Britt, 1996; Bursik, 1980; Cohen, 1986; Farrington et al., 1988; Kempf, 1987; Lattimore, Vischer, & Linster, 1994; Loeber & LeBlanc, 1990; Smith & Smith, 1984; Spelman, 1994; Stander, Farrington, Hill, & Altham, 1989; Tracy et al., 1990). Other research, consistent with the offense versatility/specialization literature, suggests that individuals who engage in one form of crime or problem behavior tend to be more likely than their counterparts to engage in other forms of crime or problem behaviors (Dembo et al., 1992; Donovan & Jessor, 1985; Donovan, Jessor, & Costa, 1988; Elliott, Huizinga, & Menard, 1989; Farrington, 1996; Gillmore et al., 1991; Gottfredson & Hirschi, 1990; Jessor, Donovan, & Costa, 1991; Klein, 1984; Osgood, Johnston, O’Malley, & Bachman, 1988; Robins, 1979; Rowe & Flannery, 1994).

In terms of the expected relationship between offense frequency and switching, we can appeal to two separate but related bodies of research. First, developmental criminologists have consistently speculated that frequent offenders are likely to be more versatile than less frequent offenders (LeBlanc & Loeber, 1998; Loeber & LeBlanc, 1990; Moffitt, 1993). They have argued
that those who initiate offending at an early age (often a good predictor of intensity or offense frequency) tend to be involved in a diverse array of offenses. Tolan (1987), for example, found that those who onset early committed an average of three different offense types per year (out of five), whereas late onset offenders committed only two different kinds of crimes (see also Elliott, 1994; LeBlanc, 1990; Mills & Noyes, 1984).

In addition to the work of developmental criminologists, those working within the criminal career tradition have indicated that offense frequency and specialization may be related. For example, self-reported data from the Second Rand Inmate Survey (Chaiken & Chaiken, 1982) suggest that high-rate offenders are more likely to be offense generalists and switch crime types than low-rate offenders. Furthermore, in a reanalysis of the Rand data, Spelman (1994) discovered that offenders who switched crime types committed about twice as many crimes as specialists, leading him to conclude that “the most frequent offenders are also most likely to be versatile” (pp. 105-107, 109). In addition, in a series of important works, Gottfredson and Hirschi (1990) have advanced the general theoretical proposition that different dimensions of criminal offending behavior likely share a common cause. This too would suggest that frequency and versatility are likely to covary in important ways.

In sum, there is a significant literature leading to the hypothesis that offenders who offend most frequently are more likely to exhibit greater versatility in their offense activity. Yet, to say that high-frequency offenders switch more frequently than low-rate offenders is not dispositive in and of itself. Because high-frequency offenders have greater opportunity to exhibit switching behavior, it is necessary to build this possibility into any analytical framework we might use to investigate the issue. The framework proposed in this article accomplishes this objective by explicitly modeling the joint distribution of offending frequency and offense switching.

**SIMULATION STUDY**

To provide an illustration of the modeling framework used in this article, we briefly describe a simulation study. Our basic objective is to estimate the probability of offense switching, \( \pi \), within two groups of offenders: (a) a large group of low-rate offenders; and (b) a much smaller group of high-rate offenders. The hypothesis of interest is whether \( \pi[\text{high rate}] = \pi[\text{low rate}] \). The first step of the simulation is to generate a dataset with \( i = 1, 2, \ldots, N = 10,000 \) observations. For each of these observations, we draw a random number \( Z_i \), where \( Z_i \sim U(0,1) \). If \( Z_i \leq .7 \), we set \( z_i = 1 \); otherwise, we set \( z_i = 2 \). This ensures that approximately 70% of the population in the simulation has \( z = 1 \), whereas the other 30% has \( z = 2 \). We can now characterize each of these observations...
with respect to two dimensions: the rate or frequency of offending acts and the number of offense switches experienced.

To simulate the number of criminal offenses, $y_i$, committed during some time period, we draw $y_i$ from a Poisson probability distribution with mean $\lambda_L = 1.0$ (if the individual is in the low-rate group, $\theta_L = 70\%$ of the population) or $\lambda_H = 3.0$ (if the individual is in the high-rate group, $\theta_H = 30\%$ of the population). Next, each observation is characterized by the number of offense transitions experienced, $T_i$. An offense transition is defined as an opportunity for a switch between offense categories to occur. An analysis of offense transitions necessitates a focus on offenders who commit at least two acts (i.e., the analysis sample is selected to include only individuals with $y_i \geq 2$). To describe an offense transition, we need to collect all $T_i$ temporally adjacent pairs of offenses for each observation. Each of these pairs of offense transitions can be denoted by $P = (q, r)$, where $q$ and $r$ are offense categories at temporally adjacent offending occasions. If $q \neq r$, then the offense transition can be characterized as a switch. If, on the other hand, $q = r$, then the transition includes repeated identical offense categories and there is no offense switching.

To generate the transitions, then, we retain only those cases where $y_i \geq 2$. For each observation, we draw $s_i$ offense switches from the binomial distribution with $y_i - 1 = T_i$ transitions and probability parameter, $\pi_i$ (where $\pi_L = .05$ for the low-rate group and $\pi_H = .10$ for the high-rate group). This arrangement implies that high-rate offenders will exhibit a greater tendency to switch between offending categories than low-rate offenders. Individuals who offend two or more times but exhibit no switches (i.e., $s_i = 0$) can be considered specialists, whereas individuals who exhibit at least one switch (i.e., $s_i > 0$) can be viewed as generalists. With $s_i$ in hand, we define a variable $g_i$ as

$$g_i = \begin{cases} 0 & \text{if } s_i = 0, \\ 1 & \text{if } s_i > 0. \end{cases}$$

Table 1 presents the distributions of $y_i$, $T_i$, and $g_i$ that result from this simulation. An objective of this study is to develop an estimator that will allow us to obtain consistent estimates of $\lambda_L$, $\lambda_H$, $\theta_L$, $\theta_H$, $\pi_L$, and $\pi_H$. A complication that we encounter in practice is that the latent tendency to commit a criminal offense (what we have termed $Z_i$) is not observed. That is, we assume that all we observe is the empirical distribution of $y_i$ (for those individuals with $y_i \geq 2$) and $g_i$. For our purposes, the estimator must recover valid estimates of the above parameters when $Z_i$ is not observed.

To account for population heterogeneity in both of these observed outcomes, we write the joint distribution in terms of a finite mixture of the product of Poisson and binomial probability mass functions. Our solution is an
extension of a set of statistical models developed by Nagin and colleagues
(Nagin, 1999; Nagin & Land, 1993). They have developed a class of finite-
mixture Poisson regression models that allow the identification of a number
of latent classes of individuals that have similar offending trajectories. For
this simulated analysis, we treat the joint distribution of \( y_i \) and \( g_i \) as the
observable outcomes from a mixture of \( K = 2 \) groups with different Poisson
and binomial processes, respectively. We write the likelihood function for
this model in several parts. First, we consider variation in \( g_i \). For individuals
with \( g_i = 0 \), the contribution to the likelihood function is
\[
\prod_{i=1}^{N} \left[ \pi_j^{g_i} (1 - \pi_j)^{1-g_i} \right]^{T_i-g_i \pi_j}
\]
and, for individuals with \( g_i = 1 \), the likelihood is given by
\[
\prod_{i=1}^{N} \left[ \pi_j^{g_i} (1 - \pi_j)^{1-g_i} \right]^{T_i-g_i \pi_j}
\]
where \( j \) denotes the unobserved group membership variable (i.e., \( Z_i = j \)). Note
that this framework explicitly allows for the possibility that some individuals
are observed to switch because they have more opportunities to switch (i.e.,
due to variation in \( T_i \)).

Next, we consider variation in the counted distribution of criminal acts, \( y_i \). Because
individuals with \( y_i = 0 \) and \( y_i = 1 \) are excluded from the analysis, we

---

**TABLE 1**

**Distributions of \( y_i \), \( T_i \), and \( g_i \) From the Simulation Study**

<table>
<thead>
<tr>
<th>Count</th>
<th># of Offenses (( y_i ))</th>
<th># of Transitions (( T_i ))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( f )</td>
<td>%</td>
</tr>
<tr>
<td>0</td>
<td>2,724</td>
<td>27.2</td>
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<tr>
<td>1</td>
<td>2,960</td>
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<tr>
<td>2</td>
<td>1,938</td>
<td>19.4</td>
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<td>3</td>
<td>1,183</td>
<td>11.8</td>
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<td>4</td>
<td>597</td>
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<td>5</td>
<td>329</td>
<td>3.3</td>
</tr>
<tr>
<td>6</td>
<td>158</td>
<td>1.6</td>
</tr>
<tr>
<td>7</td>
<td>72</td>
<td>.7</td>
</tr>
<tr>
<td>8</td>
<td>27</td>
<td>.3</td>
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<tr>
<td>9</td>
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</tr>
<tr>
<td>10</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>10,000</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Switch distribution (\( g_i \))
\[ p(g_i = 0 \mid y_i \geq 2) = .841 \]
\[ p(g_i = 1 \mid y_i \geq 2) = .159 \]
model this variable with a truncated Poisson distribution. The probability that an individual is actually included in the analysis sample is thus given by

\[ p(y_i \geq 2 | i \in j; \lambda_j) = 1 - \left[ \frac{\exp(-\lambda_j) \lambda_j^0}{0!} + \frac{\exp(-\lambda_j) \lambda_j^1}{1!} \right] \]

and the unconditional Poisson likelihood function is

\[ p(y_i | i \in j; \lambda_j) = \frac{\exp(-\lambda_j) \lambda_j^{y_i}}{y_i!} . \]

With these elements, we write the full likelihood function as

\[ L(\lambda, \theta, \pi | y, g) = \prod_{i=1}^N \left\{ \sum_{j=1}^K \left[ p(g_i | i \in j; \pi_j) \times p(y_i | i \in j; \lambda_j) \right] \right\} . \]

This likelihood function provides the basis for the analytical test proposed in this article. The basic question is whether \( \pi_j \) is equal for each of the \( j = 1, 2, \ldots, K \) latent classes or whether it is necessary to allow \( \pi_j \) to vary freely between those classes. We choose the value of \( K \) and conduct a test of the equal \( \pi_j \) hypothesis by calculating the Bayesian Information Criterion (BIC) along the lines suggested by Wasserman (1997), D’Unger, Land, McCall, and Nagin (1998), and Nagin (1999). When we apply this framework to the simulated data in Table 1, we obtain the parameter estimates presented in Table 2. Consistent with the process used to generate the data, these results indicate that the unrestricted model (which allows \( \pi_j \) to vary freely between the two classes) is the preferred model specification. We next turn to a discussion of the Philadelphia dataset used for our analysis and we then apply this same analytical framework to those data.

**DATA**

To address the research question posed by this article, we closely examine the 1945 Philadelphia birth cohort dataset assembled by Wolfgang and his colleagues (Tracy et al., 1990; Wolfgang et al., 1972). The dataset is made up of all males who were born in Philadelphia in 1945 and who resided in the city through age 17. For each of these individuals, all city police contacts through age 17 were recorded. Police contacts for criminal activity were divided into two categories: (a) contacts for serious violent crime (including homicide, forcible rape, robbery, and aggravated assault); and (b) contacts for all other offenses. Each individual is characterized by the number of police contacts experienced and whether or not at least one switch between...
the two above categories occurred. Table 3 presents the frequency distributions for each of these outcomes. Individuals with \( y_i = 0 \) and \( y_i = 1 \) experience zero transitions and are dropped from all of our subsequent analyses. This provides us with a total sample size of 1,856 individuals (out of 9,944 original cohort members).

**RESULTS**

The first step of this analysis is to estimate a reasonable specification of the mixture model for the 1945 Philadelphia data. Table 4 presents the results of our first three specifications. We begin with the simplest possible case. This is a \( K=1 \) component model where each of the \( i = 1, 2, \ldots, N \) cases contributes the product of a one-truncated Poisson probability mass function for \( y_i \) and a binomial probability mass function for \( g_i \) to the likelihood. This model assumes that there is one latent class of offenders with an average expected offending rate of 4.349 offenses per person. The remainder of Table 4 presents more complex specifications. By the BIC, the higher order mixtures in Table 4 represent a significant improvement over simpler mixtures. Indeed, by the BIC, the \( K = 4 \) component model presented in Table 4 provides the most reasonable specification of all the models from \( K = \{1, 4\} \). Because we were unable to estimate a model with \( K = 5 \) components, we settled on the \( K = 4 \) specification.

As indicated in Table 5, we estimated two versions of the \( K = 4 \) model. The proportion of cases in each of the four groups from the lowest offending rate group to the highest is 70%, 23%, 6%, and less than 1%, and their average expected offending rates are 1.156, 4.367, 11.331, and 23.451, respectively.
The first model allows the switching probability parameter, $\pi_j$, to vary freely between the latent offense frequency classes. The second model imposes the constraint that the switching probability parameter, $\pi_j$, is equal between the classes. The estimated $\pi_j$ parameters in the unconstrained model indicate that the four latent classes do not exhibit substantially different offense-switching tendencies. The probability of an offense switch on any given offense transition is .05 for the lowest rate offenders, .06 for the next lowest, and .057 for the two high-rate classes. In the restricted model, the switch probability parameter is a compromise estimate of .057. Calculation of BIC to compare these two models suggests that the restricted model is more consistent with the data. This is intuitive because the log-likelihood functions for these two specifications are virtually identical to each other, yet the unrestricted model requires estimation of three additional parameters. Our analyses would suggest that high-rate offenders are no more likely to switch offense types than low-rate offenders.

### Table 3

Distributions of $y_i$, $T_i$, and $g_i$ From the 1945 Philadelphia Birth Cohort Data

<table>
<thead>
<tr>
<th>Count</th>
<th># of Offenses ($y_i$)</th>
<th># of Transitions ($T_i$)</th>
</tr>
</thead>
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<td></td>
<td>$f$</td>
<td>%</td>
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<tr>
<td>Total</td>
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<td>100.0</td>
</tr>
</tbody>
</table>

Switch distribution ($g_i$)

$\Pr(g_i = 0 \mid y_i \geq 2) = .825$

$\Pr(g_i = 1 \mid y_i \geq 2) = .175$
The purpose of this article was to investigate the relationship between the frequency of criminal offending and the probability that an offender will make at least one offense switch between violent and nonviolent crime. Some previous work within both the life-course/developmental and criminal career

<table>
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<th>Parameter</th>
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<th>$K = 3$</th>
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<td>.051</td>
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<td>.062</td>
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<tr>
<td>Log-likelihood</td>
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<td>-4646.19</td>
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CONCLUSIONS

The purpose of this article was to investigate the relationship between the frequency of criminal offending and the probability that an offender will make at least one offense switch between violent and nonviolent crime. Some previous work within both the life-course/developmental and criminal career...
tradition has suggested that high-rate offenders might exhibit more versatile offending patterns than low-rate offenders. In an examination of this issue, our analysis examines the comparative plausibility of two different models linking offense switching and offending frequency. The first model anticipates that high- and low-rate offenders will demonstrate variation in their proclivity for versatile offending, whereas the second model predicts that high- and low-rate offenders will have similar offense-switching tendencies. Our analysis suggests that the latter explanation is more consistent with the data. In sum, it appears that high-rate offenders do not exhibit a greater tendency toward versatile offending.

To arrive at this conclusion, we generalized methods in the existing criminal careers literature on mixtures of discrete probability distributions. In so doing, we wrote down a stochastic model that allows us to address the question of interest by directly examining the joint distribution of two dimensions of criminal offending: offense switching and offending frequency. Although this model was particularly useful for our immediate interest in studying offense frequency and switching, we also think it has more general applicability for the field. For example, whereas we included all individuals who had two or more police contacts in our analysis, it is easy to think of reasons why more stringent selection criteria should be used. This would not be difficult to do with the model proposed here. Indeed, an advantage of our approach is that investigators can study increasingly selective populations. To do this, the main adjustment to our model would be to divide the unconditional offense frequency density by the probability of being included in the target population.

In addition, there is no reason that investigators should confine analyses to violent versus nonviolent categorization schemes. With the methods used here, any reasonable number of offense categorizations could be handled. In fact, increasing the number of offense categories does not affect the statistical model in any way, although the substantive results obtained with different offense categorization schemes might vary.

If we had reason to think that only some subset of the transitions should be studied, then we could evaluate the number of switches out of the number of transitions of interest. For example, if we wanted to study offense-switching behavior for only the first three transitions of an offender’s total set of transitions, then we could calculate $T_i = \min(y_i - 1, 3)$ and then $g_i$ would indicate whether an individual switched at least once during the $T_i$ transitions of interest. The subset of transitions might also be defined in terms of their content or direction as well as their number. For example, those interested in the issue of offense escalation might study only offense switches from less serious to more serious crime types.
Finally, it might be useful to decouple the offense-frequency part of the model from the offense-switching part of the model. In other words, investigators could study population variation in offense-switching tendencies as an outcome in its own right without regard to the relationship between offense-frequency and offense-switching behavior. We hope the criminology community will continue efforts to develop models like those presented here to facilitate a better understanding of key quantities involved in criminal careers.

**NOTE**

1. For example, in describing Sidney Blotzman, Shaw (1931) observed that “the record of his offenses includes a great number of delinquent practices. In fact, it would be quite impossible to make a complete inventory of all the specific instances of delinquency and crime in which he was involved” (p. 226).

**REFERENCES**


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