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Criminal career trajectories

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Abstract
This study analyzes criminal career trajectories using a unique administrative dataset of 230,578 individuals arrested and over 620,000 criminal offenses recorded by Greater Manchester Police between 2008 and 2019. Moving beyond static co-offending networks, we model individual offense sequences as transitions within a multilayer directed crime network. This allows us to capture temporal dependence and structural progression across crime types and provides a scalable method to analyze criminal trajectories at the population level.
We find that the majority of potential offenders (almost 60%) are arrested for only a single recorded offense. Among repeat offenders, specialization deepens over time: the likelihood of being arrested for the same type of crime again rises steadily across consecutive offenses, most strongly for shoplifting, burglary, and fraud. Only 9.14% of persistent offenders remain within a single crime category throughout their recorded career, making diversification the norm rather than the exception among high-frequency offenders. Within these cross-category transitions, public order offenses and weapon possession consistently precede violent crime at every career stage, suggesting structured pathways that may serve as early intervention points.

Keywords: crime networks; crime trajectories; network analysis
JEL codes: C55; C63; D85; K42

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1 Introduction

Greater Manchester Police recorded over 620,000 arrests between 2008 and 2019. The majority of individuals appear only once in the data. For those who return, whether offense sequences follow systematic patterns across crime types is a question the existing literature has addressed only partially, and rarely with data of this scale. Prior work has approached criminal careers primarily through two lenses: rational choice models emphasizing individual cost-benefit decisions [Becker, 1968], and social network analyses (SNA) focusing on co-offending structures [Charette and Papachristos, 2017, Morselli, 2009].

Applied to crime, SNA has been used to identify brokers and coordinators within organized crime groups, and to trace how network position shapes both opportunity and risk. Xu et al. [2004], for example, demonstrated how dynamic network modeling reveals shifting alliances, the emergence of key players, and organizational adaptations to internal and external shocks. Other studies, such as Bright et al. [2017]'s mapping of a drug trafficking network, have shown that structural changes following law enforcement interventions can influence both individual criminal trajectories and the resilience of criminal groups.

However, most applications of network analysis focus on relational ties between offenders rather than on the sequential structure of offenses themselves. As a result, most studies treat offense sequences and network structure separately and do not trace how offense types transition across successive arrests at the population level. We bridge this divide by modeling criminal careers as multilayer transition networks across consecutive offense events. Specifically, we examine how offense types transition across successive arrests, whether certain crime types serve as recurring predecessors to others, and whether specialization deepens over the course of a criminal career.

2 Literature

Different types of offenders, particularly when categorized by their frequency of offending, play distinct roles in the study of criminal career pathways. One-time offenders are arrested for a crime once and do not return to criminal activity thereafter. Their reasons for offending could include situational factors, momentary lapses in judgment, or unique pressures that might not persist over time [MacLeod et al., 2012]. In contrast, repeat offenders engage in criminal activities repeatedly and over extended periods. Their consistent involvement suggests deeper-rooted motivations, possible antisocial tendencies, or entrenched engagement with criminal peer groups [Lussier et al., 2017].

From a criminal career perspective, one-time offenders might not exhibit a *career* in the conventional sense, as their criminal activity is limited and often does not escalate. Conversely, repeat offenders display more discernible trajectories, with potential progressions in the frequency, seriousness, or diversification of their crimes [Weaver, 2019]. Some offenders specialize, consistently being arrested for offenses within a singular crime category, while others are versatile, transitioning between different types of crimes throughout their criminal histories [Piquero et al., 2003]. The rationale behind such patterns may be multifaceted, involving perceived ease and familiarity with particular crimes, the evolving nature of criminal opportunities, or changes in personal circumstances.

Temporally, some offenders exhibit intermittent criminal behaviors with significant gaps between offenses, reflecting periods of desistance or strategic inactivity. Others may escalate in frequency or severity, which may indicate deeper involvement in offending. Identifying these patterns has direct implications for when and how to intervene [Day et al., 2008].

2.1 Social Network Analysis and Crime

Social network analysis (SNA) enables us to map relational ties between individuals or entities, revealing underlying structures that may not be apparent through traditional methods. Through such mappings, influential nodes become identifiable—such as key brokers, coordinators, or recruiters—whose removal or incapacitation could significantly disrupt network operations [Diviák et al., 2019, Morselli, 2009]. Yet the dominant strand of this literature focuses on collective dynamics, particularly co-offending and organized crime networks, rather than on the longitudinal trajectories of individual offenders within those structures [Magliocca et al., 2021, Zakimi et al., 2023].

The traditional application of SNA has mainly focused on organized crime groups. Prior work has examined how network structures shape group cohesion, information flow, and operational efficiency. Studies have emphasized the role of peer influence and group dynamics in fostering criminal behavior, showing how network centrality and bridging positions can affect access to criminal resources, decision-making power, and vulnerability to detection [Bright et al., 2012, Calderoni et al., 2020, Duijn et al., 2014, Morselli, 2009]. These studies often conceptualize criminal behavior at the group level, focusing on collective dynamics rather than individual criminal trajectories within the network context. This leaves aspects of the longitudinal development of individual careers unexplained.

Early research into co-offending networks suggests that the strength and stability of relational ties can influence career length, specialization, and escalation [Charette and Papachristos, 2017]. At the individual level, longitudinal SNA makes it possible to track how an offender's network position shifts over time—and how those shifts relate to changes in offending patterns. Stable co-offending ties, for instance, have been linked to longer and more specialized careers [Basu and Sen, 2021].

2.2 Network Approaches to Criminal Career Progression

Network analysis has also been applied directly to offense sequences over time [Basu and Sen, 2021, Weerman, 2011]. Visualization methods have enabled researchers to document how criminal networks develop, adapt, and reorganize [Xu et al., 2004]. For example, the structural evolution of a drug trafficking organization has been mapped to show how the removal of key figures often leads to temporary instability, but can also trigger adaptive reconfigurations that preserve network resilience [Bright and Delaney, 2015].

Just as in static network snapshots, an individual's positioning significantly shapes their criminal trajectory over time. Individuals in organized crime networks often transition from peripheral to central roles as their experience accumulates, a shift typically associated with higher profits and extended career longevity [Van Koppen et al., 2010]. Maintaining stable co-offending relationships further increases the likelihood of sustained and serious criminal careers [Charette and Papachristos, 2017]. Specialization in particular crime types, such as drug trafficking or cybercrime, is associated with repeated collaboration with similarly specialized peers [Heiler et al., 2023].

We complement the existing research in three ways. First, prior work has not adequately integrated individual-level criminal trajectories into network-based analyses. This study models individual careers through temporally ordered transition matrices and directed networks. Second, we address the challenge of missing or overly aggregated data, which can obscure fine-grained behavioral patterns. Prior work has shown that even minimal missingness can distort network interpretations [Ficara et al., 2021]. By working with a large, high-resolution dataset of more than half a million criminal events, this study minimizes such limitations. Third, while machine learning and predictive analytics have been applied to static network snapshots [Bright et al., 2017], how criminal behaviors evolve over time within dynamic, structured frameworks is not fully understood. This study extends prior work by constructing multilayer temporal networks that capture transitions across up to five sequential offenses, revealing both persistence and deepening specialization patterns.

3 Data & Method

3.1 Data Overview

This study is based on a unique dataset provided by the Greater Manchester Police (GMP). It includes a comprehensive record of all arrests from April 2008 to July 2019. With the GMP jurisdiction overseeing an expansive area home to over 2.8 million people, it is one of the UK's largest police forces in terms of population. Each record includes the time and location of the arrest, the offense type, and personal details of the individual arrested, including age, gender, and ethnicity. The dataset includes 230,578 individuals arrested for 620,390 unique criminal incidents.

England and Wales employ a structured approach to categorizing crimes, often referred to as the *crime tree* categorization. This hierarchical system classifies offenses from broad categories to specific individual crimes. At the topmost level, crimes are broadly divided into Victim-Based Crime and Other Crimes Against Society. Within each of these overarching categories, crimes are further differentiated (Table 1). For the purposes of this analysis, we adapted the official 2013/14 Crime Tree by collapsing its four-level hierarchy into five broader categories. Specifically, robbery—which appears as a standalone branch under victim-based Crime in the official tree—was merged into the violent crimes category. Burglary subtypes (dwelling vs. non-dwelling) and criminal damage and arson were each collapsed into single categories. Additionally, fraud was incorporated into Other Crimes Against Society. This leaves us with five categories: Violent Crimes, Theft, Sexual Offenses, Property Damage, and Other Crimes Against Society.

Table 1: The Crime Tree, 2013/14 – Structured by Category Levels

Level 1	**Level 2**	**Level 3**
Victim-Based Crime	Violence Against the Person	Homicide Violence with Injury Violence without Injury
	Sexual Offenses	Rape Other Sexual Offenses
	Robbery	Robbery of Business Property Robbery of Personal Property
	Theft Offenses	Burglary, with a Level 4 distinction only for this crime into: 1) Burglary in a dwelling and 2) Burglary in a building other than a dwelling Vehicle Offenses Theft from the Person Bicycle Theft Shoplifting All Other Theft Offenses
	Criminal Damage and Arson	Criminal Damage Arson
Other Crimes Against Society	Drug Offenses	Trafficking of Drugs Possession of Drugs
	Possession of Weapons Offenses	—
	Public Order Offenses	—
	Miscellaneous Crimes Against Society	—

3.2 Preprocessing

Before analysis, we removed outliers and duplicates. Each arrest was then matched to an individual and ordered chronologically. The original dataset contains 382,246 person-year observations corresponding to 230,578 individuals and 620,390 unique offenses. A small proportion of records (2.74%) contained missing crime type information and were excluded from subsequent analyses. The distribution of the number of crimes per person is heavily right-skewed. 59.56% of individuals (n=137,341) are recorded with only a single offense. The frequency declines sharply as the number of offenses increases: 37,370 individuals were arrested for two crimes (16.21%), and 17,368 for three (7.53%). A small percentage of individuals were arrested for more than 50 offenses. Such accumulation can occur when multiple charges are levied simultaneously, which is typical of fraud-related crimes. For instance, a single fraudulent scheme can entail multiple counts of deception, misrepresentation, or unauthorized transactions, leading to an individual facing multiple charges simultaneously.

In total, 75% of individuals were arrested for no more than two offenses. At the 95th percentile, individuals were arrested for nine or fewer crimes, and only 1% had more than 23 offenses. To improve the representativeness of the analysis and reduce the influence of extreme values, individuals with more than 50 recorded offenses ($n = 331$, corresponding to 0.24% of individuals) were excluded from the dataset, yielding a final sample of 230,247 individuals.

We further observed some data entry mistakes in the birth year variable, where the birth year in the original dataset spans from 1901 to 2018, thus including years that do not seem plausible for a dataset spanning crimes between 2008 and 2019. Therefore, as a minimum, ages below 10 (the minimum age of criminal responsibility in England and Wales) or above 90 were excluded from mean age calculations as probable data entry errors, though the corresponding arrest records were retained in all other analyses.

3.3 Transition Matrices

We model our data as a time-inhomogeneous Markov chain, characterized by $T = 5$ transition matrices $\mathbf{M}^t \in \mathbb{R}^{N \times N}$, where $N = 20$ is the number of distinct crime types and $t \in \{1, \ldots, 5\}$ indexes sequential offense transitions. The first four matrices correspond to specific consecutive transitions (first to second offense, second to third, and so on). Transitions from the fifth offense onward are aggregated into $\mathbf{M}^5$ to avoid sparse matrices at later career stages: $n = 94{,}838$ individuals contribute at least one transition, compared with $n = 18{,}595$ who reach a sixth offense or beyond. By the fifth offense, individuals have established a pattern of persistent offending, and the marginal transitions that follow are better understood as an expression of an entrenched trajectory than as a distinct career stage.

Each entry $\mathbf{M}^t_{i,j}$ records the number of observed transitions from crime type v_i to crime type v_j at step t. The time-averaged transition matrix $\hat{\mathbf{M}}$ is computed as

$$\hat{\mathbf{M}}_{i,j} = \sum_{t=1}^{T} \mathbf{M}^t_{i,j} \tag{1}$$

Row-normalisation of $\mathbf{M}^t$ or $\hat{\mathbf{M}}$ yields the corresponding transition probability matrix. Given a count matrix $\mathbf{M}$, the probability of transitioning from crime type v_i to crime type v_j is

$$\mathbf{P}_{i,j} = \frac{\mathbf{M}_{i,j}}{\sum_{k=1}^{N} \mathbf{M}_{i,k}} \tag{2}$$

The resulting categorical distribution captures the probability that an individual was arrested for a crime of type v_j after type v_i, conditioned on that individual having been arrested for another offense at all. For each $\mathbf{M}^t$, we denote the corresponding probability matrix $\mathbf{P}^t$.

3.4 Crime Network

Transition matrices give conditional probabilities but do not provide enough insight into how common each crime actually is compared across each step. Based on the transition probabilities, we constructed a directed weighted graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ to model the criminal career trajectories. Each node $\mathbf{v}^t_i$ represents crime type i at career stage t. Each directed edge $\mathbf{e}^t_{ij} \in \mathbf{E}$ captures a transition probability from crime $\mathbf{v}^t_i$ to crime $\mathbf{v}^{t+1}_j$. Weights are defined as

$$w(\mathbf{e}_{ij}^t) = \mathbf{P}_{i,j}^t \tag{3}$$

We call these *inter-layer* edges, as they traverse between layers corresponding to time-steps. Edge width and opacity scale with raw transition counts.

The criminal trajectory of an individual is conceptualized as a subgraph $\mathbf{G}' = (\mathbf{V}', \mathbf{E}')$, where $\mathbf{V}' \subseteq \mathbf{V}$ and $\mathbf{E}' \subseteq \mathbf{E}$, representing the set of offenses and transitions made by that individual:

$$\begin{aligned} \mathbf{V}' &= \{\mathbf{v}_i^t \in \mathbf{V} \mid \mathbf{v}_i \text{ is a criminal action}\} \\ \mathbf{E}' &= \{\mathbf{e}_{ij}^t \in \mathbf{E} \mid \mathbf{e}_{ij} \text{ is a transition made by the individual}\} \end{aligned} \tag{4}$$

To capture the temporal evolution of criminal behavior, we visualize the multilayer network in three-dimensional space. The x-axis represents the sequence of offenses (i.e., t), while the y- and z-axes reflect a spring layout within each layer. Nodes are sized according to offense frequency and colored by category.

The spatial arrangement within each layer is determined by the intra-layer adjacency matrix $\mathbf{A}_{ij}^t = \sum_{t^-=1}^{t-1} \mathbf{M}_{i,j}^{t^-}$, which accumulates all observed transitions between crime types prior to stage t. This matrix is used as input to the force-directed layout: crime types connected by frequent prior transitions are placed in closer proximity.

4 Results

After preprocessing, the dataset used for analysis contained 379,496 person-year observations corresponding to 230,247 individuals and 575,888 unique offenses across 20 Level 3 crime categories (see Table 1). Among the 224,763 individuals with complete demographic records, the sample is predominantly male (73.36%, n = 164,895), with 22.91% female (n = 51,490) and 3.73% of unknown gender (n = 8,378). Valid birth years range from 1918 to 2009 (Mdn = 1984), with the largest cohorts born in the 1980s (29.87%) and 1990s (27.27%). The mean age at first offense is 30 years (Mdn = 27). All subsequent analyses draw on the full sample of 230,247 individuals.

4.1 Crime Frequency and Distribution

The offense distribution is heavily right-skewed. The majority of the individuals in the dataset were recorded with one offense (59.56%) (M = 2.59; Mdn = 1). Among repeat offenders, the mean career length is 2.28 years, though some careers extended up to 33 years.

The majority of the dataset consists of other crimes against society, violent, and theft crime categories, with each accounting for almost 30% of offenses (Figure 1). Other crimes against society offenses—comprising drug possession, drug trafficking, public order offenses, fraud, and weapon possession—constituted the most prevalent category with 172,623 occurrences (29.98%). This is very closely followed by violent crime offenses, accounting for 172,029 occurrences (29.87%), encompassing homicide, robbery, and violence with and without injury.

Theft crimes ranked third in overall frequency with 168,585 occurrences (29.27%), including shoplifting, burglary, and vehicle offenses. Property damage (criminal damage and arson) accounted for 51,970 occurrences (9.02%), while sexual offenses (rape and other sexual offenses) represented 10,681 occurrences (1.85%).

Shoplifting is the most frequently occurring offense overall (15.13%), followed by violence without injury (13.78%) and violence with injury (13.56%). Possession of drugs (10.64%) and public order offenses (10.08%) round out the five most prevalent crime types, as shown in Figure 1. The least frequent offenses in the dataset are concentrated in a small number of relatively rare but serious crime categories. Fraud accounts for 5,838 offenses (1.01%), followed by rape with 3,183 cases (0.55%). Robbery of business property represents 3,021 offenses (0.52%), while homicide comprises 2,352 cases (0.41%). Bicycle theft (1,962 offenses; 0.34%) and theft from the person (1,938 offenses; 0.34%) are the least common property crimes in the sample. The near-equal counts for bicycle theft and homicide might reflect under-reporting of bicycle theft rather than any true equivalence. While homicide can be classified as an *obligatory reporting* crime, bicycle theft is a *discretionary reporting* crime. Victims often weigh the probability of recovery against the time cost of filing a police report [Buil-Gil et al., 2021]. Sexual offenses are particularly affected by under-reporting, which means the figures here likely understate their true prevalence. Even with a relatively low number of crimes for homicide or rape, these crimes show distinct transition patterns. For example, rape has high self-transition rates that differ from the more diversified paths of high-volume crimes like general theft (see Section 4.4).

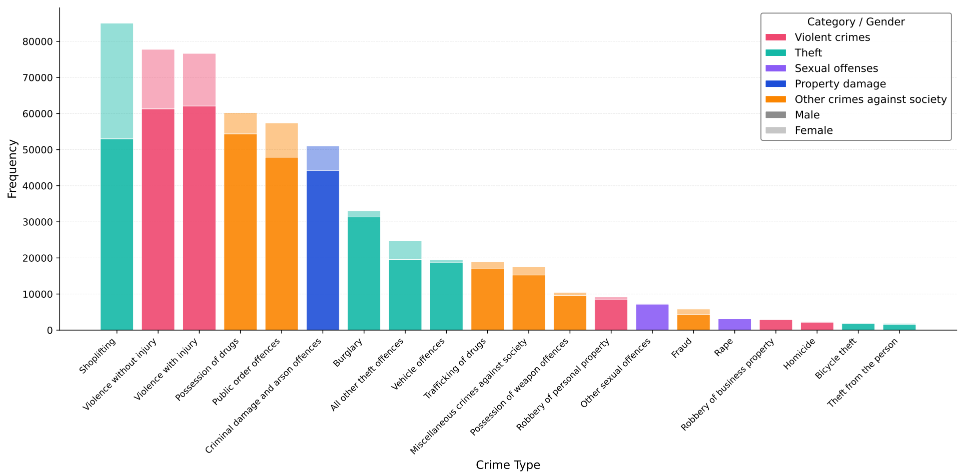

Figure 1: Frequency of crime types (color-coded by category).

4.2 First Offense Comparison: One-Time vs. Repeat Offenders

Comparing the first recorded offense of one-time offenders (n = 126,069 with a valid crime type) with that of frequent offenders (5+ offenses; n = 24,171) reveals differences in entry pathways. At the category level, one-time offenders more frequently begin with violent crimes (31.42% vs. 25.49%) and sexual offenses (2.61% vs. 1.29%), whereas frequent offenders are overrepresented in theft (32.18% vs. 24.75%) and property damage (11.23% vs. 8.16%).

At the offense level, the largest divergence is observed for burglary, which accounts for 1.55% of first offenses among one-time offenders but 7.02% among frequent offenders ($\Delta = +5.47$ pp). Vehicle offenses (1.33% vs. 4.34%) and robbery of personal property (0.44% vs. 1.92%) similarly appear more frequently as entry offenses among persistent offenders. Conversely, violence without injury (14.10% vs. 10.27%), violence with injury (16.43% vs. 12.81%), and drug possession (13.61% vs. 10.79%) are more prevalent as first offenses among one-time offenders. Shoplifting remains the most common first offense in both groups, with only a modest difference (16.74% vs. 15.02%).

4.3 Crime Co-Occurrence Patterns

Before examining temporal transitions, we analyzed the general co-occurrence of crime types within individual offending records, disregarding the chronological order of offenses. For each of the 82,078 individuals with two or more recorded crimes, we counted all pairwise combinations, yielding 1,772,942 co-occurrence pairs. To account for differences in crime prevalence, we computed observed-over-expected ratios (O/E), comparing the observed co-occurrence frequency of each pair to what would be expected if crimes were distributed independently across offenders.

At the category level, sexual offenses exhibited the strongest within-category clustering (O/E = 41.69), indicating that individuals charged with one type of sexual offense were far more likely than chance to also be charged with another. Property damage (O/E = 2.66), violent crimes (O/E = 1.74), and theft (O/E = 1.56) also showed above-chance within-category concentration, though to a lesser degree. At the level of specific offense types, the co-occurrence of rape and other sexual offenses was the most overrepresented pair (O/E = 28.58), followed by drug possession and drug trafficking (O/E = 2.61) and burglary with robbery of business property (O/E = 2.66). On the other hand, certain cross-category combinations appeared less often than expected, such as homicide and shoplifting (O/E = 0.28) or sexual offenses and theft-related crimes (O/E = 0.26–0.33). Functionally related offense types thus co-occur far more often than chance would predict.

4.4 Transitioning Between Crime Categories

To examine how crime types change over the course of a criminal career, we constructed row-normalized transition matrices for each consecutive offense pair (crime 1→2, 2→3, through 5+→next) (Figure 2). The number of individuals contributing to each transition layer decreased substantially, from 208,147 at the first offense to 82,078 at the second, and 18,595 by the sixth, reflecting the steep attrition observed in the offense count distribution. Transitions from the fifth offense onward were aggregated into a single matrix due to decreasing sample sizes at later stages.

Initial transitions. In the first transition step, many individuals re-offend within the same crime type. Self-transition rates are highest for shoplifting (0.531), other sexual offenses (0.481), and violence without injury (0.397). This means that 53.1% of offenders whose most recent crime was shoplifting will commit shoplifting again as their next offense. In contrast, categories such as theft from the person (0.126 transition to shoplifting) and all other theft offenses show a broader distribution of subsequent offenses. Drug possession also appears frequently as a second offense, particularly for those starting with criminal damage and arson (0.075), or public order offenses (0.109), pointing to some overlap between disorder-related and drug-related activity.

It is important to interpret these rates in the context of raw frequencies (Figure 1). For high-volume offenses like shoplifting, a 0.531 self-transition rate represents a large, stable cohort of repeat offenders. For less common crimes, such as other sexual offenses (0.481) or homicide (0.400), these rates are drawn from considerably smaller samples and should be read with more caution.

Cross-category transitions. Some crime types show consistent links to violent offenses across all transition steps. The transition from weapon possession to violence with injury remains stable at 0.111–0.128 across stages, and public order offenses show persistent transitions to violence without injury (0.156–0.170). Vehicle offenses appear regularly as follow-up offenses to burglary (0.069 at the first step). In contrast, sexual offenses tend to remain within their category across steps, with comparatively few links to other crime types.

Trends across offense steps. Across repeated offense steps, self-transition rates tend to increase for certain crime types, including fraud (rising from 0.332 to 0.686), burglary (from 0.277 to 0.517), and shoplifting (from 0.531 to 0.651). At the category level, theft shows the strongest increase in within-category persistence (from 0.545 to 0.712), while violent crimes remain roughly stable (0.541–0.578). The overall self-transition rate across all crime types rises from 32.29% at the first step to 39.95% at the fifth and beyond. While most offenders persist within the same category, a subset exhibits cross-category transitions—particularly from property, drug, and public order offenses into violent crime types—that remain present across all stages of the criminal career.

Among all repeat offenders ($\geq$2 crimes, n = 82,078), 32.77% remain in a single crime category. This share drops to 9.14% among persistent offenders with five or more recorded crimes (n = 24,171). Diversification becomes increasingly common as careers lengthen. The majority of repeat offenders (67.23%) cross category boundaries at some point in their recorded career.

Crime network. To complement the stage-specific transition matrices, we visualize criminal career trajectories as a multilayer network in which node size encodes offense frequency and inter-layer edges encode sequential transitions across all five career stages simultaneously (Figure 3). Unlike the transition matrices above, which aggregate all transitions from the fifth offense onward into a single final stage, the network covers only the first four transition steps (offenses 1 through 5). Later transitions are excluded to maximize both legibility and sample coverage.

At every career stage, the three largest nodes correspond to shoplifting (largest green node), violence with injury, and violence without injury (the two largest red nodes), reflecting that these are the most frequently committed crimes in the dataset. Possession of drugs and public

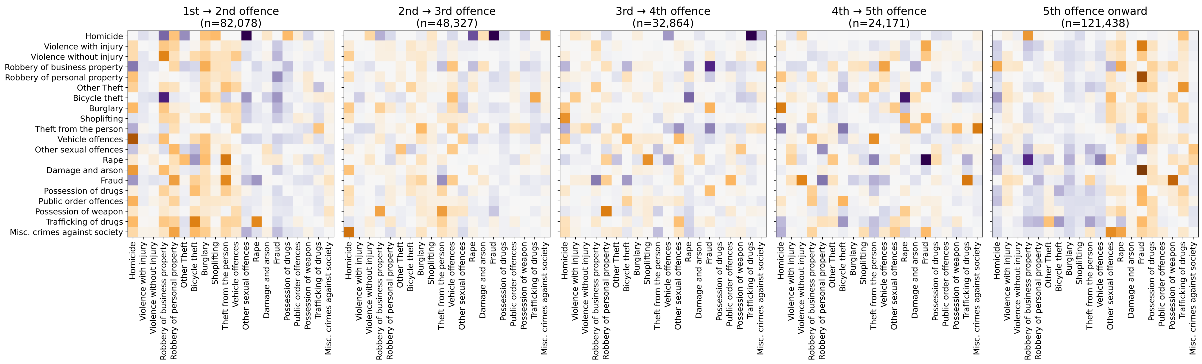

Figure 2: Row-normalized log-odds transition matrices for each offense step, compared against the time-averaged baseline. Each cell shows the log-ratio between the stage-specific transition probability and the corresponding aggregated probability across all stages. Purple cells indicate transitions that occur more frequently than the baseline at that stage; orange cells indicate transitions that occur less frequently. The diagonal is removed to focus on cross-crime transitions. The final matrix has a higher n than the preceding step because it aggregates all transitions from the fifth offense onward rather than capturing a single step.

order offenses (both orange) are the next largest nodes across all layers. The thickest inter-layer edge is the shoplifting self-transition (green), consistent with its 0.531 self-transition rate and the highest raw transition count at every career stage. This means that when a shoplifter re-offends, their next offense is also shoplifting in more than half of cases. The next thickest edges are the self-transitions of violence with injury (0.325) and violence without injury (0.397), indicating that violent offenders persist within the same type of violence rather than switching between the two. Possession of drugs and public order offenses show more moderate self-transition rates of 0.329 and 0.216 respectively, with a greater share of transitions dispersing into other crime types.

Cross-category transitions appear as edges linking differently colored nodes. Other crimes against society offenses—which include drug-related offenses and public order violations—show an 18.39% transition rate toward violent crimes, the second-largest outflow category after self-transitions. Sexual offenses retain 55.44% of transitions within category, with the remaining transitions distributed primarily toward violent crimes (17.06%) and other crimes against society offenses (16.34%).

4.5 Similarities in Recidivism Patterns per Cohort

To explore whether individuals with similar demographic or criminal backgrounds exhibit comparable patterns of re-offending, we analyzed recidivism trajectories across cohorts defined by gender, birth decade, and type of first offense ($N = 224{,}763$ individuals with ≤ 50 recorded offenses and a full demographic record). For each cohort, we constructed a feature vector encoding crime-type frequency, category distribution, self-transition rate, and mean career length, then applied PCA to project cohorts into a two-dimensional space (PC1 = 26.0%, PC2 = 14.3% explained variance).

Women ($n = 51{,}490$) show a theft-concentrated profile, with shoplifting accounting for 31.6% of all crimes and theft offenses comprising 39.6% of the category mix. Men ($n = 164{,}895$) show a more evenly distributed profile across other crimes against society (31.9%), violent (29.3%), and theft (27.0%) categories. Birth decade cohorts show a gradient across the PCA space.

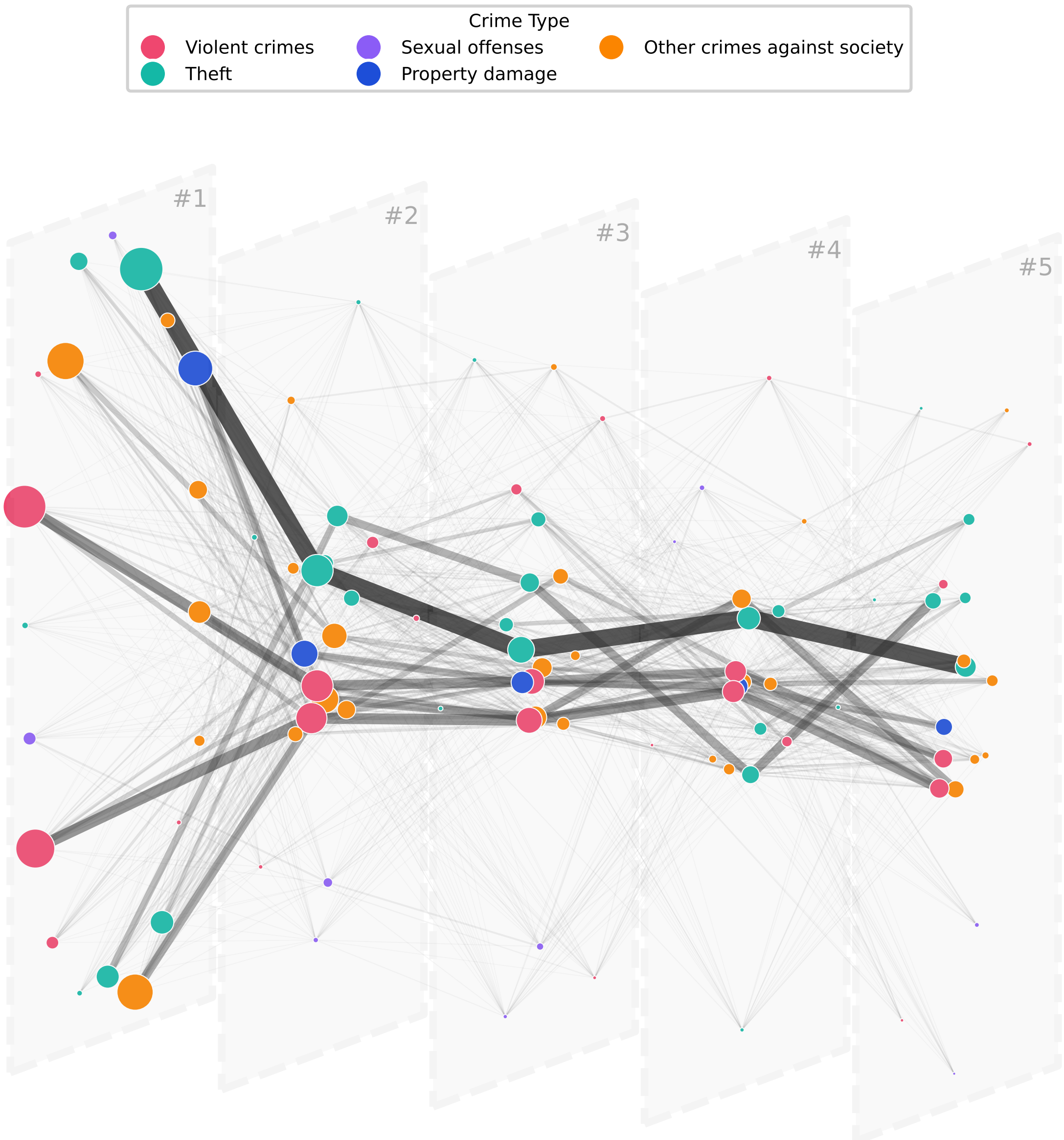

Figure 3: Multilayer network visualization showing transitions between crime types across the first five offenses. Nodes represent crime types (sized by frequency), colored by category. The largest green node represents shoplifting, the two largest red nodes represent violence with and without injury, respectively, and the two largest orange nodes represent possession of drugs and public order offenses. Gray edges show crime-to-crime transitions, with thickness indicating frequency. Vertical layers ($\#1-\#5$) correspond to offense sequence. Throughout all layers, the largest green node represents shoplifting, the two largest red nodes represent violence with and without injury.

Cohorts born between the 1930s and 1960s tend to be shoplifting-dominant and concentrated in theft and violent crime categories, and are positioned close to one another (mean pairwise distance = 3.31). Cohorts born from the 1980s onward are associated with higher proportions of violent crimes and other crimes against society offenses: among the 1980s cohort, violence with injury is the most common crime type (13.8%), and among the 2000s cohort, criminal damage and arson accounts for 19.4% of offenses, with violent crimes comprising 37.6%. These distributional differences are reflected in the distances from the 1940s–1960s centroid to younger cohorts: 5.17 for the 1980s, 7.14 for the 1990s, and 7.78 for the 2000s.

The ten closest cohort pairs further illustrate structured similarities within first-offense

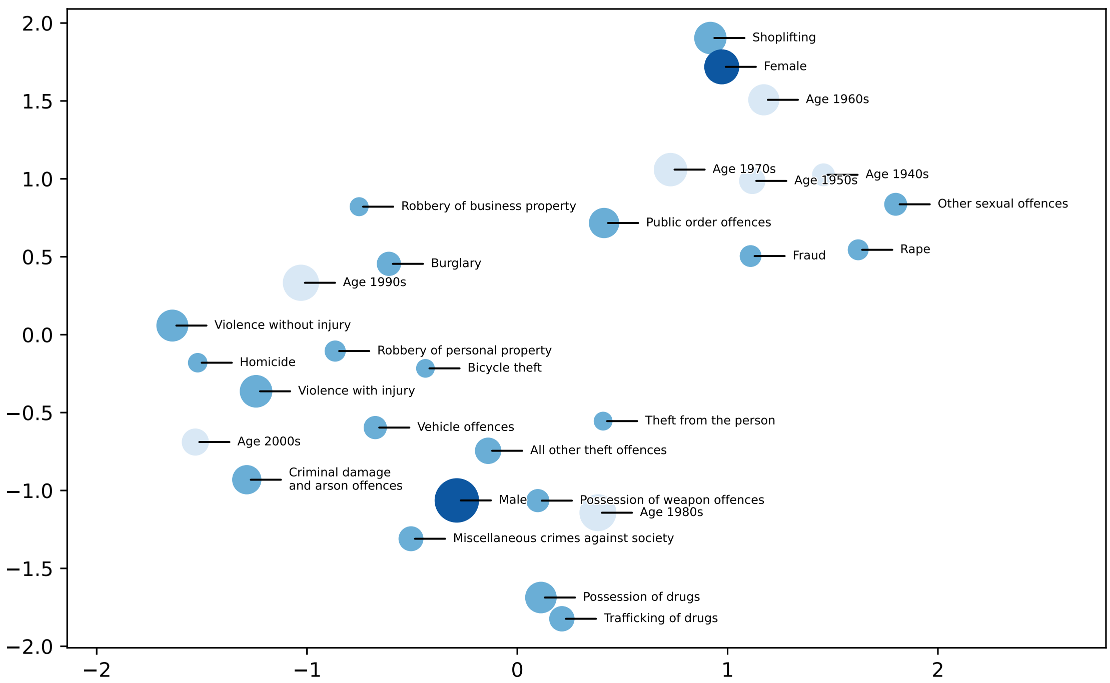

Figure 4: Patterns within distinct cohorts defined by gender (dark blue), age (light blue), and type of first offense (medium blue). Point size correlates with the number of individuals in that cohort. The axes represent the first two principal components derived from cohort-level recidivism features; proximity between points indicates similarity in the distribution and sequencing of repeat offenses across cohorts.

groupings: the two violence cohorts (first offense: violence with injury and without injury) are the nearest pair overall (distance = 0.33), indicating closely aligned subsequent offending profiles. Drug-related first-offense cohorts (possession of drugs and drug trafficking) also cluster closely together (distance = 0.63). Given that the two PCA components together account for approximately 40% of total variance, distances should be interpreted as indicative of broad structural differences rather than precise similarity measures.

4.6 Summary of Transition Patterns

Three patterns emerge from the transition analysis. First, diversification is more common than specialization among repeat offenders with more than one recorded crime: only 32.77% of those with two or more crimes ($n = 82{,}078$) stay within a single category, dropping to 9.14% among those with five or more. Over 90% of the most active offenders cross category boundaries at some point. That said, there is a clear pull back toward familiar crime types that strengthens with career length: the overall self-transition rate rises from 32.29% at the first step to 39.95% by the fifth and beyond. Acquisitive crimes show this most sharply: shoplifting self-transitions climb from 0.531 to 0.651, burglary from 0.277 to 0.517, fraud from 0.332 to 0.686. At the category level, theft shows the strongest persistence, rising from 0.545 to 0.712.

Second, how much offenders stick to a category varies considerably by crime type. Violent crimes hold steady at 0.541–0.578 across all stages. Sexual offenses are the most career-clustered (O/E = 41.69), meaning offenders who commit one sexual offense are far more likely than chance to commit another. However, the consecutive self-transition rate—the probability that the very next offense is also a sexual offense—is more moderate (0.540–0.554). Property damage has the weakest self-retention (0.241–0.283), with subsequent offenses spreading across violent crimes (33.5%), theft (23.2%), and other crimes against society (21.6%).

Third, a small number of cross-category pathways recur across all transition stages. The strongest runs from criminal damage and arson to violence without injury, holding at 0.172–0.181 throughout. Public order offenses precede violence without injury at 0.156–0.170; weapon possession leads to violence with injury at 0.111–0.128. Together, these patterns suggest that criminal careers are neither uniformly specialized nor uniformly diverse, and that the mechanisms underlying each likely differ by crime type.

5 Discussion

5.1 Specialization and Diversification in Offending

Our results provide strong evidence for both specialization and diversification in criminal trajectories. Overall, only 32.77% of repeat offenders (≥2 crimes) and 9.14% of persistent offenders (≥5 crimes) remain within a single crime category throughout their recorded career. However, we do see specialization specifically for persistent offenders who start with crimes such as shoplifting, burglary, or fraud. These individuals tend to repeat similar offenses across time, with self-transition rates rising from 0.531 to 0.651 for shoplifting, 0.277 to 0.517 for burglary, and 0.332 to 0.686 for fraud across consecutive offense steps. This is consistent with life-course criminology literature, which suggests that certain offenders—often categorized as 'career criminals'—maintain consistent behavioral profiles over time [Moffitt, 2017, Piquero et al., 2003]. High self-transition rates may reflect both personal expertise and structural opportunity: repeat shoplifters, for example, may have continued access to familiar environments and perceive lower risks of detection [Lochner, 2004].

At the same time, we also observed transitions across crime categories—particularly from criminal damage and arson into violence without injury (0.172–0.181), and from public order offenses and weapon possession into violent crime. These transitions were stable across all offense steps rather than concentrated early in the career. This points to a persistent structural link between disorder-related offending and violence, rather than a simple escalation sequence. Cumulative disadvantage models offer one possible explanation: reduced labor market access and entrenched criminal networks driving offending across crime types over time [Grogger, 1995, Laub and Sampson, 2006]. Yet if marginalization were the primary driver, we might expect these pathways to strengthen as careers progress. Their stability from the first offense onward suggests that situational and environmental factors, such as neighborhood-level exposure to violence [Papachristos, 2009], may play an equally important role in sustaining these links.

5.2 Cohort-Based Patterns and Escalation Risk

We further examined whether demographic or contextual attributes condition the pathways of recidivism. The cohort analysis revealed that demographic groups do not offend randomly: women and shoplifting-first offenders were very similar in their recidivism profiles (cosine similarity = 0.84), both clustering near the 1960s birth cohort in the PCA space and thus reflecting similar crime-type distributions and self-transition rates across their recorded careers. Women in this dataset were heavily involved in shoplifting and theft, which is consistent with a body of research pointing to economic need and limited legitimate income as the primary drivers of female offending [Giordano et al., 2002].

Individuals whose first recorded offense involved weapon possession or violence showed considerably more dispersed profiles in the PCA space, with subsequent offending spread across a wider range of crime categories rather than concentrating within a single type. This pattern is consistent with research on delinquent peer networks, where early exposure to violence both reflects and reinforces embeddedness in social environments that sustain diverse criminal involvement over time [Glaeser et al., 1996, Weerman, 2011]. Unlike the narrower acquisitive trajectories typical of property-first offenders, violence-first offenders appear less likely to settle into a stable offending niche as their careers develop.

Relatively younger cohorts—particularly those born after 1980—showed more dispersed offending profiles, with violent and other crimes against society offenses accounting for a larger share of their criminal mix than among older cohorts. Among those born in the 2000s, criminal damage and arson alone accounted for 19.4% of offenses and violent crimes for 37.6%, a very different profile from the shoplifting- and theft-dominant patterns of cohorts born before 1970. This shift may partly reflect structural changes in the UK labor market and drug trade from the 2000s onward; periods of heightened youth unemployment and changing drug market dynamics that have been linked to increased street-level violence [Machin and Meghir, 2004].

5.3 Implications for Policy

The co-existence of specialization and diversification in this dataset has direct implications for how interventions are designed and targeted. Most high-frequency offenders cannot be reached by offense-type-specific interventions alone. For high-frequency, low-severity offenders such as shoplifters—who show the strongest specialization and the clearest routinized patterns—interventions focused on disrupting opportunity structures and situational access may be more effective than those targeting individual motivation alone. The stable cross-category pathways identified here, particularly from weapon possession and public order offenses into violent crime, are present at every career stage and suggest that waiting for escalation to become apparent before intervening may already be too late. These transitions are not an early-career phenomenon that standard diversion programs would catch. Sustained engagement with high-risk individuals, rather than one-off interventions, is more consistent with the trajectories observed here [Kleiman, 2009].

Future work could enrich our approach by integrating spatial and contextual data, such as neighborhood details, policing intensity, and access to employment. This would help examine how local conditions shape the transition probabilities identified here. The sequential structure of the data also lends itself naturally to longitudinal prediction models that treat offense histories as ordered sequences rather than static profiles [Tollenaar and van der Heijden, 2013]. Both directions would move the analysis closer to the structural level, where intervention decisions are ultimately made.

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