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Target Choices of Inner-City Taggers Demonstrate Consistency and Specificity

Abstract

Offender populations are diverse, with individual offenders preferring specific target types. While extensive research has focused on high-impact crimes, the consistency and specificity of lower-impact offenses like tagging remain underexplored. Consistency refers to how stable an offender's preferred target type is, and specificity addresses whether different offenders prefer different target types. We examined these patterns among taggers, a type of illegal graffiti writers, in Ghent, Belgium, using graffiti removal data. Our dataset comprised 1,651 non-gang related tags by 248 taggers who have been observed at least twice in an inner-city area. We used the Hunter-Gaston Diversity Index (HGDI) for target preference consistency and the Weighted Nestedness Metric based on Overlap and Decreasing Fill (WNODF) for specificity. Observed values were compared with Monte Carlo simulations of random target choices. On average, each tagger produced 6.657 tags across 2.427 target categories. Most tags clustered in a few types, with 32 taggers responsible for 50% of all tags. The observed HGDI (0.587) was significantly lower than the mean simulated (0.698), indicating consistency in target preferences. The observed WNODF (26.537) was also significantly lower than the mean simulated (31.608), suggesting no collective taste but rather specificity. Our results reveal a moderate level of consistency and specificity in taggers' target preferences within an inner-city setting.

Keywords: Tagging, Graffiti, Offender Behavior, Target Choice.

Introduction

Offender populations are diverse and they are shaped, in part, by how individual offenders commit their offences, including the type of targets that they prefer. Despite this diversity, the behavior of offenders may demonstrate both consistency and specificity (Bouhana, Johnson, and Porter 2016; Canter 1995; Woodhams, Hollin, and Bull 2007). Consistency denotes the tendency for individual offenders to exhibit similar behavior across a series of comparable offences, while specificity indicates that individual offenders can be distinguished based on their particular offence behavior (Bouhana et al. 2016).

In terms of target preferences, consistency implies that individual offenders have a stable preferred target type. For example, an individual burglar may prefer to always target detached properties without visible security devices, or an individual sex offender may always prefer dark-skinned adolescent victims. Lack of consistency would imply that offenders do not have strong target type preferences and may switch target types over time. Specificity implies that different offenders have different target type preferences. For example, some burglars may prefer detached residential properties, others may prefer residential apartments, whereas still others may prefer businesses. Lack of specificity implies that all offenders have similar preferences. Consistency is a characteristic of the individual offender, while specificity is a characteristic of the offender population. Offending preferences that are both consistent and specific allow for offender profiling and population differentiation.

Most research on behavioral consistency in offenders has focused on instrumental offences with significant impact on victims, such as burglary, robbery, sexual assault, and serial homicide. Studies in these areas tend to show both consistency and specificity (Bennell & Canter, 2002; Bouhana et al., 2016; Salfati & Bateman, 2005; Woodhams et al., 2019), though the degree varies significantly across offending types (Woodhams et al. 2007). However, a gap exists in our understanding of consistency and specificity in expressive offenses, such as illegal graffiti writing in general and tagging in particular.

Illegal graffiti writing differs from instrumental crimes, such as burglary or robbery. The latter are driven by material gains, whereas illegal graffiti writing is primarily motivated by visibility, self-expression, and the acquisition of fame (Ferrell and Weide 2010; Halsey and Young 2006; McDonald 2001). Engagement in graffiti may also become addictive, as taggers develop a need for the adrenaline rush and continuous validation that comes from their work (Taylor 2012; Taylor, Marais, and Cottman 2012; Vasquez and Vieraitis 2016). More experienced and practiced writers seek recognition through “getting up”. This refers to the practice of repeatedly placing their work in various locations to increase their visibility and achieve widespread recognition from their peers (Castleman 1984; Ley and Cybriwsky 1974; Snyder 2009). Graffiti writers choose targets strategically to maximize the visibility of their work while minimizing the risk of getting caught (Castleman 1984; Ferrell 1996; Ferrell and Weide 2010; Kuralarasan, Bernasco, and Vandeviver 2024; Lachmann 1988; Mitman 2018; Snyder 2009; Vasquez, Barbieri, and Rodriguez 2021). They favor highways, overpasses, transit stations, private properties near public spaces, and smooth or hard-to-reach surfaces (McDonald, 2001, pp. 73–74; Weisel, 2013). Illegal graffiti is linked to several negative effects, such as increased crime rates (Wagers, Sousa, and Kelling 2008; Wilson and Kelling 1982), high removal costs for individuals and governments (Megler et al., 2014; Walker & Schuurman, 2015), and reduced public perceptions of safety and security within communities (Sakip, Bahaluddin, and Hassan 2016).

Illegal graffiti writing comes in a variety of forms that range from simple, quick-to-apply text-based markings, such as tags, to more elaborate, time-intensive designs (Dovey, Wollan, and Woodcock 2012). Among the various forms of illegal graffiti, tags are the most prevalent. Tags are graphic signatures written as a very fast and simple way to get a name onto a surface. Tagging is defined by its emphasis on quantity over aesthetic complexity (McDonald 2001). Taggers prioritize frequency and extensively place their name across multiple locations to maximize their visibility and recognition. Taggers who engage in repeated tagging garner respect within the graffiti subculture (Dar 2013; Lachmann 1988; Mitman 2018; Taylor 2012). Many taggers aim to achieve an ‘all city’ status by repeatedly placing their tags across multiple targets and places (“getting up”), strengthening their presence through repeated exposure (Ferrell 1995, 1996; Lachmann 1988; McDonald 2001; Mitman 2015, 2018; Powers 1996; Taylor et al. 2012; Vasquez et al. 2021; Vasquez and Vieraitis 2016)

In this study, we examine the consistency and specificity of target preferences in non-gang related tagging, a form of illegal graffiti writing, and expand the application of these concepts to expressive offences. By testing consistency and specificity hypotheses for tagging, we aim to improve our understanding of offending behavior in general and taggers’ behavior in particular. Establishing the extent of consistency and specificity in target preferences of taggers may yield insight into their target selection strategies, helping to understand what taggers define as suitable targets.

The remainder of this article is structured as follows. First, we discuss the extant research on consistency and specificity in offending behavior, distinguishing between consistency and specificity in the places, times, and targets that offenders prefer. Second, we discuss the extent to which illegal graffiti writing in general and tagging in particular could exhibit consistency and specificity in target choice. In subsequent sections, we outline our data and methods. This is followed by the presentation and discussion of our results.

Background

Consistency and Specificity in Offending Behavior

Environmental criminology explains how the interaction between routine activities and the environmental backcloth shapes patterns of offending behavior (Brantingham and Brantingham 1993; Felson and Cohen 1979), and creates the conditions for consistency and specificity in offending behavior to emerge (Bouhana et al. 2016). Like all individuals, offenders engage in routine activities, such as sleeping, working, and shopping. These activities occur at specific locations within the environment, such as an offender’s home, workplace, or a commercial district. Some locations, like their home, are unique to each offender, while others, like commercial districts, are shared by many. The engagement with these activities follows certain temporal rhythms, as offenders have individual schedules and locations have distinct operating hours.

While pursuing their routine activities, offenders become familiar with their surroundings and criminal opportunities. This so-called “awareness space” constrains where and when offenders choose to commit crimes as well as the set of potential targets. The recurring nature of their routine activities means that offenders are expected to exhibit some degree of consistency in their offending behavior. However, some degree of specificity may also be expected. Most environments have a surplus of crime opportunity types (Khorshidi et al. 2021), which allows offenders to exercise individual preferences when choosing specific targets (Woodhams et al.

2007). Thus, the same environment might contain multiple groups of offenders with distinctive target preferences.

The decision to exploit a crime opportunity is framed within the rational choice perspective (Cornish and Clarke 1986). This perspective suggests that offenders weigh the potential risks and rewards of their actions. Rather than acting impulsively, they evaluate factors such as visibility, accessibility, likelihood of detection, and personal gain—albeit boundedly and momentarily. This perspective assumes that offenders make purposive choices, selecting targets that maximize material, symbolic, or reputational benefits while minimizing the risk of getting caught or failing.

Extensive research shows that offenders prioritize offending in familiar areas (Bernasco, 2010; Bouhana et al., 2016; Deslauriers-Varin & Beauregard, 2014). For example, they prefer locations nearby their residence (Bernasco and Nieuwbeerta 2005; Rengert and Wasilchick 1985; Wright and Decker 1994). Offenders have been found to have characteristic offending ranges (Barker 2000), with shorter crime trips being more common (Rossmo 2000; Vandeviver et al. 2015). Beyond distance, consistency is also evident in offenders' travel directions and routes (Van Daele and Bernasco 2012). Research further indicates that some degree of spatial specificity exists as well. Offenders exhibit individual preferences for specific crime locations (Frith, Johnson, and Fry 2017; Townsley et al. 2015) and crime distances (Townsley and Sidebottom 2010).

Research also shows that offending behavior exhibits a degree of temporal consistency (Deslauriers-Varin and Beauregard 2013; van Sleeuwen, Steenbeek, and Ruiter 2021; Sorochinski et al. 2023). Daily and weekly routines shape offenders' exposure to criminal opportunities, leading to a preference for committing crimes at specific times and days. For example, serial sexual offenders consistently prefer to offend at specific times (Lovell et al. 2022) and days of the week (Hewitt et al. 2022). Notably, van Sleeuwen et al. (2018, 2021) found repeat offenders committing crimes at more similar hours of the day and days of the week than expected. The observed temporal consistency was most pronounced for the same type of offence and when less time had elapsed between offences (van Sleeuwen et al. 2021).

Research into the extent of target consistency is limited and gives rise to mixed findings (Woodhams et al. 2007). Nevertheless, some studies provide evidence that target choice for the same offence type may exhibit consistency. In particular, research on repeat victimization suggests that the same offender may repeatedly target the same victim or target (Bernasco 2008; Pease 1998). For example, burglars consistently target the same type of house (Bouhana et al. 2016), favoring houses with similar layouts on the same side of the street (Bowers and Johnson 2005) and with specific physical attributes (Armitage 2006). In the case of homicide, more than half of serial offenders repeatedly targeted victims of the same gender and race/ethnicity (Salfati et al. 2015). Similarly, Chan et al. (2015) found that Canadian serial sexual homicide offenders have specific victim-type preferences, although not all serial sexual offenders are consistent in their victim choice (e.g., Lovell et al., 2022).

Target Consistency and Specificity in Illegal Graffiti Writing and Tagging

Target selection of illegal graffiti writers reflects an interplay of visibility, risk management, and subcultural dynamics. Exposure is a key motivation for graffiti writers, but risk is considered as well (Ferrell 1995, 1996; Halsey and Young 2006; Kuralarasan et al. 2024; Lachmann 1988; McAuliffe 2015; Mitman 2018; Powers 1996; Taylor et al. 2012; Vasquez and Vieraitis 2016). Urban features such as bridges and intersections are preferred targets for illegal graffiti writers due to their high visibility and reduced interruptions, allowing them to

acquire visibility while managing risk (Ferrell and Weide 2010; Kuralarasan et al. 2024). This balance between visibility and risk may imply a certain degree of consistency in target preferences, as writers may consistently favor targets situated in locations that maximize public exposure while minimizing the likelihood of detection (Ferrell 1996; Halsey and Young 2006; Lachmann 1988; Mitman 2018; Powers 1996; Taylor 2012; Vasquez et al. 2021). Meanwhile, the subcultural emphasis on fame and recognition may also drive differentiation in target preferences (Ferrell 1996; Powers 1996; Snyder 2009). This could imply specificity within the graffiti community as individuals select targets that are suited to their skill, audience, and reputation. In this way, graffiti writers seek to claim space and gain individual recognition (Halsey and Young 2006; Ley and Cybriwsky 1974; Mitman 2018; Vasquez et al. 2021)

Nevertheless, existing research on graffiti writers gives rise to mixed expectations with regard to levels of consistency and specificity in their target selection (Ferrell and Weide 2010; McDonald 2001). Whether different graffiti writers could be distinguished based on their target choices (specificity) is not clear. Several factors might contribute to potential uniformity in target preferences among graffiti writers. Shared knowledge and practices within the subculture could play a significant role. Graffiti writing skills and target evaluation criteria are transmitted through peers and learned collaboratively (Mitman 2018; Van Loon 2014; Vasquez et al. 2021). This can lead different graffiti writers to develop similar preferences for target types. For example, graffiti writing techniques are often learned and refined within the community. This could result in a common preference for targets with particular surfaces or textures. Additionally, graffiti writers may share information about highly desirable targets that maximize exposure and minimize risks (DeShay, Vasquez, and Vieraitis 2021; Mitman 2018). This shared knowledge could lead to a convergence in target selection, as graffiti writers seek out similar targets. Furthermore, the strong sense of community and shared subcultural norms and values (Ferrell and Weide 2010; Van Loon 2014) can further reinforce common target selection preferences in graffiti writing communities. For example, exposure is key and applying graffiti to targets in highly visible spots or high-risk areas might be seen as a way to gain respect and recognition (Ferrell 1996). This could lead to a uniform preference for such targets (Lachmann 1988; Van Loon 2014). Peer learning and collective taste could thus contribute to shaping uniformity in target selection among graffiti writers.

At the same time, individual characteristics and motivations might contribute to differences in target type preferences. Experience and risk tolerance could influence target choices as well as differences in skill level, desired audience, and desire to gain recognition by demonstrating artistic craftsmanship (Ferrell and Weide 2010; Halsey and Young 2006; McAuliffe 2015; Schacter 2008; Young 2017). For example, novice, lower skilled writers who seek to make a name for themselves might prefer targets with smoother surfaces at more conspicuous or risky locations, such as public buildings or busy transportation hubs, reflecting their limited networks and local focus (McAuliffe 2013, 2015). Conversely, more experienced and skilled writers with an established reputation might prioritize targets with surfaces that offer a larger canvas for their artwork at locations that are less conspicuous. These decisions align with the norms of graffiti culture, which emphasize respect for the hierarchy of writers and assess urban surfaces based on their visibility, nature, and accessibility (Ferrell and Weide 2010; Halsey and Young 2006; Young 2017).

In addition, ecological dynamics might be at play as well. Suitable targets may be limited and competition between graffiti writers could give rise to differences in target type preferences as writers aim to maximize visibility and recognition within the subcultural hierarchy (Campos 2013; Ferrell and Weide 2010; Van Loon 2014). For example, similar to how coexisting species reduce the potential impact of competition through partitioning of resources (Roughgarden 1976), different graffiti writers might prefer different target types to avoid competing for the

same target types. Some writers might focus on high-visibility targets to gain fame and recognition, while others might choose other spots to showcase their artistic skills without competition.

While these studies provide insights into how target consistency and specificity might emerge in graffiti writing more generally, including tagging, target consistency and specificity of tagging behavior in particular may be additionally affected by elements specific for tagging. Taggers prioritize rapid execution, high frequency, and maximized visibility over artistic complexity (Kindynis 2018). Tags are often opportunistic rather than carefully planned (Van Loon 2014). This may be because tags are faster and simpler to create compared to other forms of graffiti, which allows taggers to complete their work quickly and leave the location rapidly. Although the opportunistic and transient nature of tagging may render risk management less important for taggers, research indicates that taggers consider the risk of detection and tag removal. For example, environmental risks such as lighting and CCTV are taken into account (Vasquez et al. 2021). Juvenile taggers use strategies to reduce detection risks, such as tagging in locations with fewer observers, at dusk, and having lookout partners (DeShay et al. 2021). Taggers also prefer spots such as freeway billboards and underpasses, where their work is likely to remain visible while their tagging activity remains discreet. They tend to avoid targets in areas that are frequently cleaned by authorities, as these are perceived as high-surveillance zones. Consequently, removal programs may influence which targets taggers prefer. Furthermore, taggers exhibit territorial behaviors in their target selection. Most taggers prefer targets that already contain tags, suggesting that they may mark over existing tags to assert their dominance, strengthen their status (Haworth, Bruce, and Iveson 2013). Tagging the same surface repeatedly strengthens their status and recognition in the graffiti subculture. Taken together, this may imply that taggers may be less discriminate in their target preferences which could give rise to low degrees of target consistency and specificity in tagging.

Drawing on these insights, we examine the structure of target preferences in taggers by considering the extent to which they are consistent and specific in their target preferences. We aim to answer the following two research questions:

1. Consistency: To what extent are taggers consistent in their target preferences, and
2. Specificity: How are target preferences structured within the tagger population?

By addressing these questions, we aim to contribute to the broader understanding of behavioral consistency and specificity in offender populations, specifically within the context of tagging.

Data

Our data are derived from 2,323 non-gang related tags removed by the city administration of Ghent, Belgium, from January to December 2016. The city operates a graffiti removal program that involves a zone-by-zone approach, prioritizing graffiti in the historic city center and recurring graffiti (City of Ghent 2015). A dedicated team catalogs and removes graffiti, and property owners can report graffiti for removal. Although there is no strict time frame for the removal cycle like other cities (e.g., Halsey and Young 2002; Iveson and McAuliffe 2022), graffiti are addressed systematically. Gang related graffiti have not been observed in Ghent for over a decade (Kuralarasan et al. 2024).

Tags are characterized by the use of unique aliases and occasionally distinct aesthetics (Campos 2013; Lachmann 1988; McDonald 2001; Powers 1996). Tags and the use of aliases are textbook examples of consistency and specificity distinctiveness. Taggers use the same style and alias for their graffiti, and their aesthetics will be distinct from each other. In graffiti subcultures, aliases are personal. Plagiarizing another tagger's alias is discouraged and would not contribute

to individual status and recognition (McDonald 2001). Mimicking another tagger's alias is challenging, as taggers adopt unique and complex aesthetics. Therefore, tags allow us to distinguish between individual taggers without the need to identify them personally.

Although comprehensive, our dataset does not cover all tags in the city. It includes instances detected by the removal team or reported by property owners and subsequently removed. This means that unreported tags, due to varying graffiti tolerance levels across the city, and tags reported but not removed due to city administration priorities, such as the focus on removing graffiti in the historic city center, are not captured. This pattern aligns with Cresswell's (1992) observations on urban spatial dynamics and socio-cultural perceptions of graffiti, which influence where graffiti is reported and removed. Considering these factors, we focus on the inner-city. This decision, based on Haworth et al. (2013), aimed to provide a more unbiased representation of tagging activity and an equitable operating environment for all taggers. Areas prioritized for graffiti removal efforts tend to be dominated by tags, rather than different forms of graffiti (Haworth et al. 2013). We defined the inner-city as an 8 km² area bordered by an 11 km ring road, coinciding with the city's historical borders.

Each tag was coded using removal photographs to capture the alias used, and the object or surface upon which the tag was written (i.e. target). To maintain focus in the analysis, prevent excessive categorization, and ensure a sufficient sample size, tags were not differentiated based on their size or type of material used to leave the tag (e.g., paint, marker, stencil, scratching, paper/wheat paste, textile, or other). Twelve unique target types were identified based on thematic similarity of the object or surface upon which the tag was written (e.g., exposed walls, doors, traffic signs; for a full overview, see Table 1). In light of our interest in the level of within-individual variation in target type selection, we need to be able to observe whether taggers prefer similar target types across multiple instances of tagging. Therefore, our analysis includes only taggers whose tags have been observed at least twice. This criterion aligns with definitions of active taggers in graffiti literature (Vasquez, Barbieri, and Rodriguez 2021). Methodologically, observing at least two instances per individual is the minimum requirement to be able to identify variations in individual preferences, and is consistent with methods used in behavior consistency research (e.g., Lovell et al. 2017). The final sample consists of 1,651 tags, representing 248 distinct taggers active in the inner-city.

Methods

We deploy one metric that measures the diversity in resource use amongst individuals in a population, and one metric to measure the structure of resource preferences in the population. First, to quantify the diversity of chosen target types of individual taggers, we use the Hunter-Gaston Diversity Index (HGDI) (Hunter and Gaston 1988). This index measures inconsistency, so it increases with decreasing consistency in target choices. To gain insight into the collective behavior of the tagger population, we aggregate these individual-scale measurements. This involves calculating the mean and standard error of the HGDI score across all individuals, thereby allowing us to assess and interpret target consistency at the population level. The HGDI metric provides insight into the individual consistency of target type preference. Second, to understand how target type choice differences are structured in the population of taggers, we use the Weighted Nestedness metric based on Overlap and Decreasing Fill (WNODF) (Almeida-Neto and Ulrich 2011). WNODF allows us to evaluate whether target type choices of more consistent taggers are subsets of less consistent taggers, helping us to understand to what extent there is a structured pattern in how taggers prioritize certain target types. All analyses are implemented in R version 4.2.2 (R Core Team 2022). We developed a custom

function to calculate the HGDI and utilized the vegan package (Oksanen et al. 2024) to compute the WNODF.

HGDI has been used to measure diversity in ecological environments. When applied to taggers, HGDI measures the degree of inconsistency in target type choices by individual taggers, quantifying the diversity of their target type preferences. The HGDI formula is expressed as:

$$HGDI = 1 - \left(\frac{1}{N(N-1)} \sum_{j=1}^J T_j(T_j - 1) \right) \quad (1)$$

Where N is the total number of target choices made by the individual, T_j represents the number of times a specific target type j is chosen by the individual, and J is the number of different target types. This formula calculates the probability that two randomly selected tags (from the same taggers, and without replacement) are of a different type. HGDI values range from 0 to 1. A score of 0 indicates complete consistency, and implies that a tagger consistently chooses one specific type of target. Conversely, a score of 1 indicates complete inconsistency, and implies that a tagger chooses a different type of target for every new tag they paint. If taggers are highly inconsistent in their choices, it reflects a preference for maximal variability in target type selection. If a tagger has no preference, their choice is random and their HGDI would be in between 0 and 1, depending on the distribution of target types in the population. The HGDI is a variation of the Simpson Index (also known as Herfindahl Index and Blau Index). In the Simpson Index, the term $N(N-1)$ is replaced with N^2 , so that both measures asymptotically converge with increasing N . We prefer the HGDI here because in our data most taggers have a relatively small number of tags (6.657 on average).

Individual consistency in target type preferences implies that taggers have preferences that are stable over time. Individual consistency does not necessarily imply that all taggers have the same preferences. Two taggers can be individually consistent, but disagree completely on what target types are attractive.

WNODF is a measure to assess the degree of agreement (i.e. lack of specificity) in target type preferences between taggers. Unlike the HGDI, which describes the choices of individual taggers, the WNODF is a measure that applies to the population of taggers as a whole. In ecology, nestedness refers to a situation where interactions between species and their environment are hierarchically organized, with the interactions of a subset of elements contained within the interactions of a larger set of elements. The WNODF is calculated using the formula:

$$WNODF = \frac{2(WNODFr + WNODFc)}{m(m-1) + n(n-1)} \quad (2)$$

In this formula, m corresponds to the number of rows (taggers), and n corresponds to the number of columns (target types). $WNODFr$ and $WNODFc$ represent the weighted nestedness for rows and columns, respectively, indicating the shared target types between pairs of taggers. Specifically, we structure the matrix such that each row corresponds to a tagger and each column corresponds to a target type, with entries showing the number of times that a specific tagger selected that specific target type. The matrix can be sorted in several ways to reveal patterns of nestedness. Rows can be sorted by their richness, representing how many target types each tagger selected, with taggers who selected the most target types appearing first. Similarly, columns can be sorted by their richness, representing how many taggers selected each target type, with target types chosen by the most taggers appearing first. A combination

of both sorting criteria can also be applied, such as sorting first by column richness and then by row richness, or vice versa. These sorting criteria help to highlight overlap and decreasing fill, making patterns of nestedness more evident. *WNODFc* is then calculated as:

$$WNODFc = 100 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \frac{k_{ij}}{N_j} \quad (3)$$

where k_{ij} is the number of cells in column j with counts less than the cells in column i , and N_j is the number of non-empty cells in column j . *WNODFr* is computed analogously swapping comparison columns with comparison of rows. The *WNODF* formula accounts for both the overlap (how many targets are shared between pairs of taggers) and decreasing fill (the extent to which the target preferences of one tagger encompass the preferences of another), quantifying the degree of nestedness in the target choices of taggers.

WNODF values range from 0 to 100, where 0 indicates no nestedness and 100 indicates perfect nestedness (Britton, Almeida Neto, and Corso 2016). Strong nestedness in tagging implies that there is a general consensus among taggers on the attractiveness or utility of certain target types, leading to similar rank ordering of preferences. Many taggers' target choices are subsets of the choices made by other taggers, suggesting a shared set of common "core" targets chosen by many taggers. For example, if taggers collectively prefer target types in a specific order (e.g., $A > B > C > D$), and assuming scarcity of target types, we expect to observe individual target type patterns like A, AB, ABC, and ABCD in the population, indicating these shared preferences. Conversely, weak nestedness implies heterogeneous target type preferences, reflecting a diversity of rank orders between taggers, such as $A > B > C > D$ for some taggers coexisting with $D > A > C > B$ or $B > C > A > D$, etc. for other taggers. Thus, we might expect to see target patterns like A, AB, ABC, ABCD alongside other patterns like D, DA, DAC and DACB. Target preferences in the population would be strongly nested in the first case, and weakly nested in the second case (i.e., targets chosen by individuals preferring $D > A > C > B$ are not a clean subset of the targets chosen by individuals preferring $A > B > C > D$). Understanding these patterns of nestedness is crucial for our study as it reveals the underlying structure in the choices of taggers, shedding light on the extent to which there is agreement between taggers about the attractiveness of target types. This understanding contributes to our broader research goals of comprehensively analyzing taggers' behavior and preferences. For example, weak nestedness might point to partitioning of resource niches to reduce competition among taggers (Brantingham 1998; Roughgarden 1976). That is, taggers preferring $A > B > C > D$ would less frequently encounter and compete over target sites with taggers preferring $D > A > C > B$ compared with other taggers also preferring $A > B > C > D$.

To evaluate the significance of the observed patterns in our data and determine whether these patterns reflect a true underlying process or are likely due to chance, we employ a **null modeling** approach (Gotelli and Graves 1996). This approach establishes a baseline for assessing whether the observed values for our metrics—HGDI and *WNODF*—exceed null expectations under neutral conditions. The null hypothesis assumes that taggers are neutral regarding their target type preferences, meaning they do not prefer any target type over another, nor do they develop preferences over time.

Our null modelling approach involves creating a null model that accounts for the observed activity levels of the taggers and assumes that taggers select target types proportional to their total occurrence in the observed data. To account for the activity levels of the taggers, the null model preserves the row sums of the data matrix. This allows to randomly sample as many

target types as the number of tagging instances that are observed for each individual tagger. Random sampling occurs with replacement to reflect a scenario where all target types are widely available and do not become exhausted. This allows for taggers who favor a particular target type to repeatedly choose the same target type. Therefore, in our null model, each tagger is allowed the possibility of selecting the same target type multiple times. The probability of target type selection is:

$$P(a_{ij}) = \frac{T_j}{N} \quad (4)$$

Where a_{ij} is a cell in the data matrix, T_j is the total for column j , and N is the matrix total. This model reflects the availability of target types based on their observed frequency in the data, with selection probabilities detailed in Table 1, row ‘Proportions’.

This model corresponds to the SIM4 null model algorithm (fixed row sums, columns proportional) described by (Gotelli, 2000, p.2609). To implement the null model, we use a Monte Carlo resampling procedure with 1,000 iterations. For each iteration, we simulate taggers selecting target types based on the assumptions of the null model.

As a robustness check, we examined whether variations in the minimum targets per tagger (3, 4, 5) impact the outcomes of our analysis. Our results remain consistent across these alternative target minima (see Table A1 in Appendix). This indicates that the choice to consider taggers with varying degrees of engagement does not affect the outcome of our analysis and that our conclusions are not sensitive to changes to the minimum number of targets per tagger. Given this consistency and to maintain simplicity, we focus on the results associated with taggers who have been observed at least twice.

Results

Distribution of Target Types and Taggers

On average, within the subset of taggers who had two or more tags, taggers were responsible for 6.657 tags (sd = 10.716) across 2.427 different target types (sd = 1.348). Table 1 shows the target types and their proportions in the dataset as well as the proportions of taggers who exploited each target type. The majority of observations were concentrated on a small number of target types, with exposed walls (44.58%, $n = 736$) and transformer boxes (29.56%, $n = 488$) making up more than 70 percent of all instances of tags. Exposed walls were targeted by 79.44 percent ($n = 197$) of all taggers, transformer boxes and doors were targeted by 58.87 percent ($n = 146$) and 34.68 percent ($n = 86$) of all taggers, respectively. Figure 1 shows the distribution of instances of tags by taggers. Looking at the distribution of taggers across target types (see Table A2 in Appendix), 62 taggers limited their target choice to a single target type, and a maximum of seven target types were selected by at least two distinct taggers. Together, these summary statistics indicate that a small number of target types were repeatedly chosen by a small number of highly prolific taggers.

Table 1. Target Types, Counts and Proportions

[Insert Table 1]

Figure 1. Lorenz Curve of Tag ($n = 1,651$) Distribution Among Taggers ($n = 248$)

[Insert Figure 1]

Figure 2 presents the distribution of taggers based on the number of unique target types they engaged with. The distribution indicates that most taggers limited their tagging to one or two target types, even though there is a small proportion of taggers who engaged with up to seven target types: 40.23 percent ($n = 100$) engaged with two different target types, while only 0.81 percent ($n = 2$) engaged with seven target types. Interestingly, 25 percent ($n = 62$) of all taggers limited their tagging against a single target type. This highlights a trend where individual taggers concentrate their efforts on a limited number of target types, suggesting a preference for specific target types rather than versatility across a wider range of target types.

Figure 2. Target Type Exploitation Among Taggers ($n = 248$)

[Insert Figure 2]

Diversity and Consistency of Target Preferences

Figure 3 **Error! Reference source not found.** presents the mean observed HGDI values across all taggers in the population as well as the average and distribution of simulated HGDI values, generated from 1,000 independent simulations. In these simulations, taggers are assumed to be neutral with regard to their target preferences, randomly selecting target types from the observed distribution (displayed in Table 1). The simulated mean HGDI value is 0.698 ($sd = 0.022$). Visual inspection of the mean observed HGDI value of 0.587 ($sd = 0.382$) suggests only a moderate degree of target diversity among the taggers compared to the simulation baseline. However, the observed degree of diversity is, in fact, significantly lower ($p < .001$) and therefore unlikely to arise by chance from a population with no actual target preferences. Figure 4 presents the between-person variability in observed HGDI values among 248 taggers.

Figure 3. Mean Observed ($n = 248$) and Mean Simulated ($k = 1,000$) Hunter Gaston Diversity Index (HGDI) Values

[Insert Figure 3]

Figure 4. Between-Person Variability in Observed ($n = 248$) Hunter Gaston Diversity Index (HGDI) Values

[Insert Figure 4]

Structure and Specificity of Target Preferences

Figure 5 compares the observed WNODF (25.537) with the average WNODF (31.608, $sd = 0.951$) derived from 1,000 independent simulations. The histogram shows the distribution of WNODF values from the simulations based on neutral target preferences. The observed WNODF value of 25.537 suggests a relatively small degree of nestedness in the target preferences of taggers. However, the observed WNODF is significantly ($p < 0.001$) lower than the average simulated WNODF of 31.608. It can be inferred that the taggers in our study display a more individualized and less nested target selection pattern than what would be expected under neutral target preferences. While there are some shared target choices among the taggers, many of them have distinct preferences, not just being subsets of the choices made by other taggers. The divergence from the simulated WNODF further emphasizes that the target choices of taggers in this study are unlikely to be nested and not attributable to chance, and more

characteristic of selective preferences. In other words, these taggers display a high degree of specificity relative to a simulated baseline based on no systematic target type preferences.

Figure 5. Observed ($n = 248$) and Mean Simulated ($k = 1,000$) Weighted Nestedness metric based on Overlap and Decreasing Fill (WNODF) Values

[Insert Figure 5]

Discussion

Our study investigated taggers' target selection, a relatively unexplored area in criminology. We examined to what extent taggers are consistent and distinctive in their target preferences and addressed two key questions: To what extent are taggers consistent in their target preferences (consistency), and how are target preferences structured within the tagging population (specificity)? To answer both questions, we used graffiti removal data from the historic city center of Ghent, Belgium, focusing on non-gang related tagging involving aliases. We analyzed 1,651 non-gang related tags performed by 248 taggers between January and December 2016. To quantify the consistency and specificity of target preferences among these taggers, we applied the Hunter-Gaston Diversity Index (HGDI) to measure consistency, and the Weighted Nestedness Metric based on Overlap and Decreasing Fill (WNODF) to measure specificity.

We found a moderate yet substantive degree of consistency in target selection among individual taggers. The observed HGDI value of 0.587 is significantly lower ($p < .001$) than the simulated mean HGDI of 0.698 ($sd = 0.022$). This suggests that individual taggers do not randomly select target types but instead display stable preferences for certain target types. This resonates with Bouhana et al. (2016), who emphasize that even amidst the versatility of criminal behavior, individuals can demonstrate a consistent *modus operandi*. Contrary to assertions that graffiti writers who employ name-based graffiti randomly select targets (Ferrell 1996; Van Loon 2014), our results indicate a moderate degree of consistency in their target type choices and suggest a more structured approach in target selection among taggers. This aligns with research by, inter alia, Bennell & Canter, (2002) and Woodhams et al. (2007, 2008), which points to distinct and consistent patterns in offending behavior. Thus, our research contributes to a better understanding of tagging behavior, indicating that target selection, even in seemingly impulsive acts such as tagging, is likely influenced by a deliberate and potentially systematic process. Our findings of non-random and selective target choice among taggers also contribute to a more general understanding of offender behavior. For example, our analysis reveals patterns in tagging that mirror those identified in crime linkage studies (Bennell and Canter 2002; Woodhams et al. 2007). The observed non-randomness in target selection by taggers presents an opportunity to apply crime linkage techniques for identifying and understanding tagging patterns in urban areas, particularly through the analysis of repeated targeting of specific types of locations or surfaces. Such an approach could help researchers uncover the underlying preferences or motivations of taggers, and possibly graffiti writers more broadly.

By applying WNODF, we also shed light on the structure of target preferences among taggers. Our findings reveal that the observed WNODF value (25.537) was significantly lower ($p < .001$) than the simulated mean (31.608, $sd = 0.951$). This implies a relatively low degree of nestedness in target preferences among taggers, and is evidence of a substantive amount of specificity in target preferences of taggers. It suggests that target preferences among taggers are individualized rather than collective. This challenges a wider held notion within graffiti

research that graffiti writing communities, such as taggers, develop a ‘collective taste’ for what makes targets suitable (e.g., Campos, 2013; Ferrell & Weide, 2010). We found that target preferences of taggers exhibit specificity. This is in line with earlier studies that demonstrated significant individual differences in spatial target preferences of instrumental offenders such as burglars (Frith et al. 2017; Townsley et al. 2016; Townsley and Sidebottom 2010). Furthermore, the divergence from the simulated mean WNODF underscores that the target choices of taggers in our study are unlikely to be nested and cannot be attributed to chance. Instead, these choices are indicative of divergent preferences among the taggers. This understanding of target selection patterns in tagging speaks to the broader need for a more individualized approach in analyzing offending behavior, moving beyond the general assumptions of commonality within specific offender categories.

Several mechanisms could contribute to our observed levels of consistency in target choice. Routine activities and familiarity with areas and targets may be one mechanism that drives consistency. Taggers operate within their awareness space—areas they traverse regularly when completing their routine activities (e.g., routes to school, work, or social hangouts). Familiarity with the physical layout, timing of pedestrian and vehicle traffic, and presence or absence of surveillance within these areas may make it easier and safer to return to similar targets in those areas, contributing to consistency in target choices. Risk minimization could be another mechanism that contributes to consistency. From a rational choice perspective, once a tagger identifies a target type that offers high visibility and low risk of apprehension, they may be more likely to stick with it. Returning to familiar target types may help to reduce uncertainty and increase efficiency, as the tagger has already assessed the risk-reward balance. Self-efficacy, and feedback and reinforcement could further drive consistency. Taggers may gravitate toward target types that match their physical ability, artistic skill, or preferred tools (e.g., McAuliffe 2013, 2015). Successfully tagging similar targets may boost confidence and reinforce the perception that such targets are “doable,” further promoting consistency. Moreover, if previous tags on a specific target type remain visible over time, this may provide positive reinforcement and could encourage similar choices in the future (DeShay et al. 2021). Conversely, rapid removal may discourage certain types of targets, reinforcing preferences for other target types. Subcultural dynamics specific for graffiti writing and tagging, such as gaining recognition and claiming space, may be a fourth mechanism at play. Within graffiti subcultures, the choice of target can signal a tagger’s status or stylistic identity (Ferrell and Weide 2010; Halsey and Young 2006; Kindynis 2018). Consistency in target types may serve to strengthen personal “branding” within the graffiti scene, reinforcing reputation and recognition among peers. Taggers may repeatedly tag within certain areas or on specific surfaces to mark territory or assert presence (Haworth et al. 2013). Returning to the same types of targets may help maintain visibility in key locations and could signal control over a particular space. These mechanisms are neither exhaustive, nor are they mutually exclusive. Additional mechanisms may be involved, such as the development of cognitive scripts for tagging and tagging similar targets becoming habitual behavior rather the outcome of new situational evaluations. Moreover, these mechanisms may work in combination. For example, a tagger might habitually tag transformer boxes along their daily route (routine activity), because it is low-risk (rational choice), matches their skill set (self-efficacy), and helps build a recognizable presence (subcultural dynamics).

Observed levels of specificity could be shaped by similar mechanisms. Personal identity and subcultural meaning may contribute to specificity. Tagging is often a form of self-expression (Taylor 2012; Vasquez and Vieraitis 2016), and taggers develop distinct aesthetic identities (McDonald 2001) which could extend to their choice of target surfaces (Halsey and Young

2006; Kindynis 2018). Moreover, different target types carry different symbolic meanings in graffiti culture (Kindynis 2018; McDonald 2001). A tagger may prefer tagging certain target types (e.g., public vs. corporate-owned) based on ideological, political, or aesthetic motivations. These personal value systems could influence target specificity. Individual ability could be another mechanism that contributes to specificity. Taggers select targets that match their individual abilities and skill (McAuliffe 2013, 2015). For example, a novice tagger might prefer sleek, vertical surfaces because those are easier to tag (e.g., traffic signs), while a more experienced tagger may favor target types with textured surfaces that are more difficult to tag (e.g., brick walls). Competition could be a third mechanism that drives specificity. In environments where multiple taggers operate, competition for prime targets may be intense (Campos 2013; McDonald 2001; Van Loon 2014). When many taggers are competing for visibility and recognition in the same geographic area, standing out becomes crucial. This can lead taggers to differentiate their target preferences in ways that reduce overlap with others. Analogous to resource partitioning in ecology (Roughgarden 1976), where competing species develop specialized niches, this process may contribute to the development of individualized target preferences as a strategic response to competition that allows to maximize individual exposure and recognition. Taken together, these mechanisms may help to provide an initial understanding of why taggers can be distinguished based on their target type preferences, even when operating within similar environments.

In addition to offering a foundation for exploring the mechanisms that may contribute to the observed patterns of consistency and specificity, our findings have several theoretical implications for environmental criminology and tagging research. First, our findings suggest that the rational choice perspective may be applicable to tagging behavior. Evidence of consistency suggests that tagging is not random or opportunistic (Kindynis 2018; Van Loon 2014), but may reflect rational, repeated evaluations of suitable targets. This aligns with the rational choice perspective, which posits that offenders weigh risks and rewards (Cornish and Clarke 1986). Repeated selection of certain target types implies that taggers may learn over time which targets best balance visibility and risk, and that focusing on specific targets could serve as a heuristic in their decision-making. Second, our findings warrant extensions of target selection theories to expressive offenses. Much of the research on target selection focuses on instrumental offenses such as burglary or theft, where targets are chosen for material gain. Tagging is an expressive offense driven by non-material motives such as visibility, self-expression, or fame (DeShay et al. 2021; Taylor 2012). Consistency in target choice suggests that tagging also exhibits structured, purposive behavior. This calls for adaptations of target selection theories that account for symbolic, aesthetic, and reputational factors to adequately capture the decision-making of expressive offenses such as tagging. Finally, heterogeneity in offender decision-making may need to be more explicitly considered in environmental criminological research. Specificity in tagging behavior points to individual-level variation. This heterogeneity in offender decision-making is often overlooked in environmental criminological research (but see Frith et al. 2017; Townsley et al. 2016; Townsley and Sidebottom 2010). Our findings highlight the need for models that account for inter-offender variation.

Our findings also carry several practical implications for graffiti prevention and management. First, the observed consistency in taggers' target preferences suggests that hardening specific surface types—rather than applying broad, uniform strategies—may be effective in deterring prolific taggers. For example, if a tagger repeatedly targets traffic signs, applying anti-graffiti coatings to those surfaces could reduce their tagging activity. This focused target hardening approach may also be more resource-efficient than general deterrent measures. Second, the

finding that 25% of taggers focus exclusively on a single target type points to a subset of offenders who may be especially vulnerable to disruption. For these individuals, rapid and repeated cleaning of their preferred surfaces could be particularly effective. As DeShay et al. (2021) note, taggers tend to avoid surfaces that are frequently cleaned, making persistent and rapid cleaning a potentially effective deterrent. Fourth, the specificity observed across taggers highlights the potential for tailored prevention strategies based on surface type. Since taggers exhibit distinct preferences for particular target types, and the availability of these target types often varies across urban contexts, a uniform prevention strategy may not effectively deter all subgroups. Rather than treating all graffiti targets the same, interventions could account for the characteristics of each target. For example, metal traffic signs in transit hubs may require different strategies than concrete walls in residential areas, as they attract different types of taggers with distinct motivations and risk perceptions. Finally, our findings suggest that diversifying legal graffiti spaces could support more taggers. Instead of just offering large walls, which may not appeal to all taggers, introducing a greater variety of target types in these legal spaces, such as traffic signs, utility boxes, or other commonly tagged objects, could make them more attractive to a broader range of taggers. By aligning legal opportunities with taggers' diverse preferences, such initiatives might be more effective to help redirect some individuals away from illegal graffiti to legal expression.

Our study has certain limitations. First, we focused on identifying patterns of consistency and specificity in target selection of taggers, without directly examining the underlying mechanisms that could contribute to these patterns. Future research could build on our findings and proposed mechanisms by investigating the motivations and decision-making processes that shape individual tagging practices. Qualitative approaches, such as in-depth interviews with taggers or ethnographic fieldwork, may be well-suited to explore these mechanisms to learn directly from taggers to what extent our proposed mechanisms contribute to consistency and specificity in tagging behavior. Second, our emphasis on tagging limits the generalizability of our results to this specific type of graffiti. Whether similar results would apply to other forms of graffiti remains uncertain and could be explored in future research. Tagging is a quick and simple way to mark a surface. This makes a variety of target types suitable for it. However, more complex and elaborate forms of graffiti might require different target types which could affect the consistency and specificity of target selection. For example, smaller targets such as traffic signs, parking meters, and garbage cans may be suitable for tagging but not for more complex forms of graffiti. Nonetheless, taggers also engage in other forms of graffiti (McDonald 2001), suggesting that the individual characteristics and motivations that influence consistency and specificity in target preferences for tagging may also apply to other graffiti forms. Third, we considered only tagging activity within the city center. Taggers prioritize visibility and recognition (Campos 2013; DeShay et al. 2021; Ferrell 1996). This makes densely populated areas with high pedestrian traffic, such as city centers, attractive to taggers—and suitable for our study. However, this focus could introduce bias because the opportunity structure for tagging and the exposure to suitable targets could differ outside the city center, where footfall and visibility are comparatively lower. Additionally, taggers may behave differently outside the city center due to lower levels of surveillance and fewer removal activities. For example, risk-tolerant taggers might prefer tagging in city centers for higher exposure despite greater removal efforts, while risk-averse taggers might choose outlying areas with lower exposure but easier conditions. Future research could explore graffiti target selection more broadly and at broader spatial scales to assess whether our findings hold across diverse urban contexts. Fourth, we assumed taggers use unique aliases. However, some taggers may adopt multiple aliases, for example, when experimenting with a new style or experiencing police pressure (McDonald 2001). This means that we may have fewer than the 248 individual taggers identified in our

663 1,651-tag sample. This could affect our estimates of consistency and specificity. It is unclear
664 how this impacts our results, as taggers with multiple aliases might choose similar or different
665 target types across their aliases. Future research could examine to what extent taggers who adopt
666 multiple aliases exhibit consistency and specificity in target choices across their aliases. Finally,
667 relying solely on graffiti removal records may introduce bias as unreported instances of tagging
668 are excluded. Combining removal records with systematic social observation to record tags that
669 remain unreported to city administrations can provide a more comprehensive pattern of tagging
670 activity. Nevertheless, our conclusions only apply to patterns of tagging within known events.

671 In conclusion, we contributed to understanding target selection among taggers in an inner-city
672 urban setting. Our analysis revealed a moderate level of target consistency and specificity
673 within this population, shedding light on the decision-making process of taggers and
674 challenging previous assumptions of randomness in graffiti writers' behaviors. More broadly,
675 our findings further highlight the importance of considering both individual and collective
676 patterns in understanding the consistency of offending behaviors in urban contexts.

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