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ORIGINAL PAPER

Co-offending and the Persistence of Violence: A Dynamic Analysis

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Abstract

Objectives Previous research underscores the influence of prior violent co-offending on subsequent violent behavior, linking it to a social contagion mechanism akin to the internalization of violence. However, these studies are limited by disregarding the entirety of a criminal career and overlooking diverse co-offending dynamics beyond co-offenders' characteristics. This study examines the longitudinal impact of prior violent (solo and co-) offending on future individual-level violent behavior among Italian organized crime offenders.

Methods Leveraging criminal career data from 9819 Italian organized crime offenders, we model offending choices through a discrete-time Markov process. Subsequently, employing dynamic random-effects probit models, we quantify the influence of prior violent (solo and co-) offending on future violence, considering various confounders and unobserved individual-level effects.

Results Violence is a persistent and long-lasting behavior among organized crime offenders. Prior violent co-offending has a greater impact than prior violent solo offending on the probability of future violence. Prior violent co-offending increases the probability of future violent co-offending but does not impact the probability of future violent solo offending.

Conclusions The results show that co-offending promotes the transmission of violence but fail to support the internalization of violent behavior postulated by prior studies. We propose possible alternative mechanisms of violence transmission that operate through self-sustaining dynamics of violent co-offending within criminal groups. Although limited data on individual characteristics constrains interpretation, our results imply that violence transmission dynamics are independent from the individual characteristics of the co-offenders and more directly connected to group effects.

Keywords Co-offending · Violence · Collective behavior · Dynamic models · Organized crime

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Introduction

Research on violence increasingly emphasizes the role of relational factors in explaining violent behavior. Rather than focusing on individual and ecological determinants, many scholars now recognize violent behavior as a dynamic process of interactions with others (Papachristos 2009). Studies show that violence is often persistent (Campana and Giovannetti 2020; Hodgins 2007; Niezink and Campana 2022) and that co-offending influences it in multiple ways. The presence of co-offenders facilitates the commission of violent crimes (McGloin and Piquero 2009; McGloin and Thomas 2016; Rowan et al. 2022) and the transmission of violent behavior to previously non-violent individuals (Campana and Giovannetti 2020; Conway and McCord 2002; Niezink and Campana 2022). However, the specific mechanisms through which co-offenders transmit violence remain partially unclear. Most prior research theorize violence transmission from a dynamic perspective in terms of a contagion process, where violence spreads from an individual to the other (e.g., through co-offending); the "infected" individual then internalizes the violent feature and engages in this behavior alone. In this study, we find that alternative mechanisms may be at work.

We rely on data on the criminal career of 9819 organized crime offenders in Italy. We use the term 'organized crime' to characterize a set of stable organizations whose members act in concert to systematically engage in crime (Paoli and Vander Beken 2014; United Nations Convention against Trasnational Organized Crime 2004). Our dataset contains information on members of Italian mafia organizations, which can be considered as a specific form of criminal organizations that not only systematically engage in crime, but also engage in 'illegal governance', i.e., they exercise quasi-political functions and control legitimate markets in their areas of settlement (Aziani et al. 2020; Paoli 2014). In this study, however, the illegal governance dimension peculiar to the mafias is only marginally related to dynamics of violence and co-offending. We consider that our large sample offers a unique opportunity to examine the interaction of violence and co-offending within groups, with insights that may potentially extend to other types of organized criminal groups. Both violence and co-offending are defining features of the behavior of most organized crime offenders. Violence is essential to engage in illicit markets, to provide private protection, and to compete with rival criminal groups (Arlacchi 1994; Blok 1975; Gambetta 1993, 2009; Paoli 2003). 'Co-offending' is the act of committing a crime in cooperation with one or more accomplices (Reiss 1988). Felson argued that "organized crime is a form of co-offending" (Felson 2009, p. 160). By definition, individuals involved into organized crime are posited to cooperate with other members in the commission of offenses; however, offenders who are part of an organized criminal group have diverse criminal careers that include crimes committed both within and outside the scope of the criminal group's activities, and both can be solo or co-offenses (Meneghini and Calderoni 2022).

Organized crime research has until recently focused more on analyzing violent outcomes at the group level rather than studying individual-level characteristics of offenders (Kleemans and van Koppen 2020). As a result, there is limited research on transmission of violence and co-offending within criminal organizations (Meneghini and Calderoni 2022; Voce et al. 2021). This research gap prevents a better understanding of the interrelated dynamics of co-offending and violence within specific social contexts offering repeated interaction and violent offending opportunities. Participants in organized crime groups have dense social relations, and these may favor co-offending. Recent research suggests that co-offending among organized crime is common and only moderately declines with age and criminal experience (see, for example, Meneghini and Calderoni (2022)).

However, it is unclear whether the frequent co-offending patterns exhibited within criminal groups promote the same violence transmission dynamics observed in other samples.

To examine these issues, we model how offending choices evolve over time by adopting a dynamic step-by-step approach. Specifically, we consider how engaging in violence and committing crimes with others at a certain point in time impact the probability of engaging in violence in future offending. In other words, we focus on how offending events at time t (including violence and co-offending) impact violent offending at $t + 1$ and $t + 2$. This is a major innovation compared to prior studies on the dynamic impact of violent co-offending, which in most cases divided the criminal career into two distinct time windows and estimated the impact of interaction with violent co-offenders in the first period on violent outcomes in the second period. Our methodological framework allows to model violent offending as a gradual process that capitalizes on previous violent interactions. We then rely on dynamic random-effects probit models to quantify the impact of previous violent offending on current offending behavior while accounting for different confounders. We find that previous violence has a lasting and cumulative impact on current offending behavior, that prior violent co-offending has a greater impact on the probability of future violence compared to prior solo offending, and that such impact of prior violent co-offending is driven by a direct impact on future violent co-offending—while there is no impact on the probability of future violent solo offending. We compare our results with prior research on violence contagion and discuss how our findings indicate that the internalization of violent behavior may not be the only mechanism of violence contagion: in our sample, group processes that facilitate violence exhibit self-sustaining dynamics. Ultimately, our work contributes to the strand of research on co-offending's impact on the developmental course of criminal behavior.

Background

Violence and collective behavior

Violent crimes are often committed by cooperating offenders (Lantz 2019; McCord and Conway 2002; McGloin and Piquero 2009; Tillyer and Tillyer 2019). This is true for all crimes falling under the category of violent offenses, except for sexual assaults and other sex crimes (Bright et al. 2020; Carrington 2009; van Mastrigt and Farrington 2009). Scholars have explained this finding by referring to mechanisms of "collective behavior" (McGloin and Piquero 2009; Warr 2002): when committing a crime with accomplices, individuals lighten their responsibility for the illegal act by blaming the others, thus engaging in behavior that they would not have done if alone (Festinger et al. 1952; Wallach et al. 1964; Zimbardo 1969). Some authors defined this mechanism as a process of "diffusion of responsibility" by which the offenders perceive a lower individual responsibility for their actions (Reiss and Farrington 1991; Rowan et al. 2022; Wallach et al. 1964; Warr 2002). This explains why violent offenses—generally considered more morally unacceptable compared to other crime types—are more likely to be committed by co-offenders. From a theoretical point of view, sharing the responsibility for an illegal act with others can reinforce the neutralization techniques proposed by Sykes and Matza (1957) and Matza (1964), such as denial of responsibility and denial of the victim. Denial of responsibility occurs when offenders claim that they were forced into situations out of their control, while denial of the victim happens when they believe that victims deserve the crime committed (Matza 1964). The presence of accomplices may sustain these psychological rationalizations.

These theories found indirect and direct support in subsequent research. In terms of indirect evidence, both McGloin and Piquero (2009) and Tillyer and Tillyer (2019) demonstrated the existence of a relationship between the likelihood to co-offend and/or the number of co-offenders and violent crimes. Other works directly demonstrated the relation between co-offending and the diffusion of responsibility. For example, McGloin and Thomas (2016) conducted an experiment showing that as the group size increases, respondents perceived higher excitement and inclusion, lower risk of getting caught, and lower responsibility for the criminal act. Rowan and colleagues (2022) examined longitudinal data on first time offenders and found that the perceptions of responsibility decreased when the crime was committed in the company of others, when it was not solely their idea, and as the group size increased.

Overall, this strand of research examined the psychological mechanisms when committing a violent crime with others and showed that these mechanisms depend on group dynamics and are independent of the specific characteristics of the co-offenders (McGloin and Piquero 2009). Yet, this research suggests that the impact of group dynamics is static, that is, it occurs at the same moment of the individual's choice to engage in violence. However, other studies show that collective behavior processes also have a dynamic effect, with prior interactions with others affecting future violent behaviors. We turn to this discussion in the next section.

The dynamics of violence: contagion and persistence

Social and criminal contact might also support violent offending from a dynamic perspective: today's relationships can impact tomorrow's individual choice to commit violence. Research addressing the dynamic perspective focused on the "spread of violence" or a proper "violence contagion" or "diffusion", i.e. an individual internalizing and adopting a specific behavior following close interaction with individuals who had already exhibited the behavior (Burt 1987; Fagan et al. 2007).

The concept of violence contagion is theoretically rooted in the core arguments of Sutherland's differential association theory (1947) and the further developments of social learning theory proposed by Akers (1977, 1998). Criminal interaction with others provides techniques for misbehaving, which the individual might not otherwise have learned, as well as motives and rationalizations for certain illegal behaviors (Sutherland 1947). Co-offenders can influence the offending path of group members through learned norms and values, behavioral reinforcement, and modeled behaviors (Akers 1977, 1998). Similarly, McCord's construct theory (1997) argues that contact with co-offenders can provide potentiating reasons for each offender to consider deviant or illegal behavior as plausible.

Contagious interactions are various. For example, Bond and Bushman (2017) showed that violence spreads among US adolescents through friendship relations: individuals were more likely to engage in violent behavior if their friends did so, and violence contagion extended up to 4 degrees of separation for certain types of serious violence (i.e., 4 social connections—a friend of friend of friend of friend), although its impact decreased with the degrees of separation. Social contagion may also derive from conflict relationships: for example, in the gang context violence is often used in a reciprocal manner to settle disputes, defend one's reputation and respond to prior attacks (Papachristos 2009; Papachristos et al. 2013), thus occurring in "an epidemic-like process of social contagion" (Papachristos et al. 2013, p. 74).

A few studies focused on co-offending relationships as transmitters of violence. Conway and McCord (2002) firstly tracked longitudinal patterns of violence (over an 18-year period): they found that juveniles with no history of violent offending, and whose first co-offense was committed with violent accomplices, were more likely to commit a subsequent violent crime compared to those not exposed to violent co-offenders. They ascribed this finding to a form of social contagion, by which individuals learn and acquire a proclivity for violence through the social exchange of shared criminal behavior. However, their sample included only 235 target offenders and their accomplices, and they focused on co-offending only in the first committed offense. In examining violent attacks with injury in the UK, Campana and Giovannetti (2020) found that violence is persistent at the individual level, as previous involvement in violence is the strongest predictor of future violence. After accounting for previous violent behaviour, prior co-offending with a violent offender also increased the probability of future violent offending, proving that a process of violence contagion is at work. However, the study split the data into two time periods and aggregated criminal information within each period. Niezink and Campana (2022) applied relational event models to crime events involving UK organized crime offenders. Results confirmed that previous violence fosters future violence at the individual level. They also showed that previous co-offending relationships may lead to violence not due to mechanisms of social learning (Akers 1977, 1998) but following prior co-offending turning sour (i.e., offenders are at risk of violent victimization coming from individuals who have been their co-offenders).

Overall, this literature showed that previous co-offending favors future violent behavior through mechanisms of social contagion. The contagion idea implies a process of internalization of violent behavior: similarly to epidemics, following an at-risk contact, the individual adopts the feature or behavior that the contact has transmitted to them (Burt 1987; Fagan et al. 2007). Compared to other interactions, co-offending reported particularly strong violence contagion effects, as it directly provides the individual with a live example to emulate (Bandura 1986; Bright et al. 2024, Walters 2020). However, previous research failed to consider the entire criminal career, or merely divided it into a "pre" period (in which individuals are exposed to co-offenders' influence) and a "post" period (in which the violent outcome may manifest). Moreover, research often disregarded other co-offending dynamics that may influence violent behavior beyond the characteristics of the co-offenders (e.g., whether they are "violent" co-offenders). An interesting exception is a study by Walters (2020) that found that co-offending led to increased moral disengagement in the future, which in turn positively affected future delinquency. In other words, moral disengagement mediated the relationship between co-offending and future crime, as the association with delinquent peers led to the internalization of norms and attitudes that facilitate future delinquency. This result was independent from the characteristics of the co-offenders and points to a persistent impact of collective behavior and diffusion of responsibility dynamics, which extends to future offending behavior.

The current study

In this paper, we study the longitudinal impact of violence and co-offending on future individual violent behavior. Previous studies among different offending samples found that social interaction through co-offending can lead to an increased probability of future violence

(Campana and Giovannetti 2020; Conway and McCord 2002; Niezink and Campana 2022). We contribute to this strand of research by considering whether similar dynamics apply also to offenders who are part of organized criminal groups.

We use data on a specific offending sample—organized crime offenders—for whom both co-offending and violence can be considered constitutive features of their criminal behavior. Organized crime offenders engage in some co-offending by definition (even though co-offending does not account for all the crimes they commit: see, for example, Meneghini and Calderoni (2022)); at the same time, the ability to resort to violence is considered crucial to run the illicit business of private protection and compete with rival criminal groups (Arlacchi 1994; Blok 1975; Gambetta 1993, 2009; Paoli 2003).

We also introduce some methodological innovations to the way violent behavior and co-offending are modelled compared to previous research on the topic: we rely on Markov models and dynamic probit models to analyze the stepwise probabilities of being in certain "states" (i.e., committing a specific offense type with or without the company of others) conditional on the offender's prior state. These statistical tools allow to conceptualize gradual changes in offending over the life-course, assuming that previous criminal behavior affects current offending decisions. Given that organized crime offenders are embedded in a criminal context that encourages persistent levels of offending, it seems pertinent to rely on this type of models that allow to analyze the step-by-step consequences of offending with others, rather than focusing on the long-term impact of certain behaviors (e.g., by looking at the cumulative impact of a co-offense on all the subsequent crimes committed as done by previous studies on this topic).

Our analysis has two objectives: (1) Analyzing how violence unfolds over the criminal career of organized crime offenders and whether it is a persistent behavior; (2) Evaluating the impact of committing violent offenses with accomplices on the future probability to commit violence. Considering our stepwise approach to model the probability of committing violence, we use $P\left(X_t|W_{t-1}\right)$ to indicate the conditional probability of event X happening in t given that event W happened in $t-1$. We write Y_t^V to define a violent offense committed at time t, Y_t^C a violent co-offense, and Y_t^S a violent solo offense. Based on previous theoretical and empirical findings, we formulate the following hypotheses:

1. At the individual level, violence is a persistent behavior: $P\left(Y_t^V|Y_{t-1}^V\right) > P(Y_t^V)$.
2. The persistent effect of violence lasts for more than two consecutive offenses: $P\left(Y_t^V|Y_{t-1}^V, Y_{t-2}^V\right) > P\left(Y_t^V|Y_{t-1}^V\right) > P(Y_t^V)$.
3. Due to this persistent effect of violence, we hypothesize that also the violent co-offending and the violent solo offending processes are persistent, and this persistence is lasting: $P\left(Y_t^C|Y_{t-1}^C, Y_{t-2}^C\right) > P\left(Y_t^C|Y_{t-1}^C\right) > P(Y_t^C)$; $P\left(Y_t^S|Y_{t-1}^S, Y_{t-2}^S\right) > P\left(Y_t^S|Y_{t-1}^S\right) > P(Y_t^S)$.
4. Because prior evidence suggests a contagion effect following group violence, we hypothesize that violent co-offending increases the probability of future violence compared to violent solo offending: $P\left(Y_t^V|Y_{t-1}^C\right) > P\left(Y_t^V|Y_{t-1}^S\right)$; $P\left(Y_t^V|Y_{t-1}^C, Y_{t-2}^C\right) > P\left(Y_t^V|Y_{t-1}^S, Y_{t-2}^S\right)$.
5. We hypothesize that due to mechanisms of violence contagion, offenders internalize violent behavior after committing violence in the company of others, and thus that violent co-offending increases the future probability of violent solo offending: $P\left(Y_t^S|Y_{t-1}^C\right) > P(Y_t^S)$.

Data and methods

The PMM data set

Our analysis relies on the PMM (Proton Mafia Members) data set, a longitudinal data set containing information on the entire criminal careers of 11,138 convicted mafia offenders in Italy.[1] The inclusion criterion for the PMM is having at least one final conviction for the crime of mafia association, provided in Article 416-bis of the Italian Criminal Code. This offense criminalizes the participation in a mafia association, defined as a criminal association whose members use the intimidatory power of the association and the consequent conditions of subjection and silence (the so-called *omertà*) to perpetrate serious offenses and obtain other unjust advantages (see La Spina 2014, p. 594).[2] For each individual included in the PMM data set, we retrieved information on any conviction across their life course, for any type of crime, related or not to mafia involvement. The data set includes information on 178,427 final convictions, including the year of crime commission, the type of offense, and whether the crime was committed in cooperation with others.[3] The data set also reports the sex, and year and province of birth of each offender.

The PMM data set comprises offenders born in different years and pools them together as an artificial cohort. The oldest offender in the data set was born in 1927 and the youngest one in 1994, while over 80% of the offenders were born between 1950 and 1980. Historical events and policy changes occurring over this time span (and especially in the early 1980s, see La Spina 2014) have affected the law enforcement's capacity to record and punish violent offending and cooperation in crime. As an example, the mean individual co-offending prevalence among offenders born from 1970 onwards is 68.14% versus 54.51% for offenders born prior to 1950. Among other measures, the offense of mafia association criminalized the participation in mafia-type organizations starting from 1982 (La Spina 2014). To focus on a more consistent sample in terms of criminal careers' exposure to law

[1] The PMM data set was developed within the framework of the research project PROTON, funded by the European Union's Horizon 2020 research and innovation program under grant agreement number 699824. For additional information on the PMM data set and an overview on the criminal careers of the Italian mafia offenders see Meneghini et al. (2023) and Savona et al. (2020).

[2] The criminal liability for the mafia association offense is independent from the liability for the specific offenses individuals may commit to pursue the goals of the mafia association. For example, a participant in a mafia association perpetrating extortions for the organization will be charged for both the mafia association offense and the extortion offenses. The criminalization of the participation in a criminal association separately from the specific offences is established in most criminal legislations across the world. While civil law countries have included general criminal association offences since the nineteenth century, common law countries have more recently introduced similar general offenses, partly due to the influence of international legal treaties such as the UN Convention against Transnational Organized Crime or European Union legislation (Calderoni 2012; Schloenhardt et al. 2023, Chapter Article 5).

[3] The data set reports information on co-offending by indicating whether, for each crime, the offender was also jointly sentenced for Article 110 of the Italian Criminal Code, which sets provisions for offenders who cooperated in the commission of a crime. Article 110 states that "whenever more individuals contribute to committing the same offense, each of them is subject to the punishment imposed for that offense". This provision outlines a broad concept of co-offending, which encompasses all forms of cooperation between offenders, including those in which one offender contributed only in a minimal part to the realization of the crime. The execution of the crime (and thus the actual cooperation of offenders) can also be fragmented in time, and some offenders may only bring a moral contribution to the realization of the crime (e.g., by participating in the planning of the offense). That said, the norm requires for each jointly convicted offender the intent to cooperate with the other accomplices, thus formally excluding offenders involved in situations of conflict (e.g., two or more actors that are the opposing factions in a violent crime event) from being considered co-offenders.

enforcement action, we excluded offenders born prior to 1950, whose careers have a more limited overlap with laws and policies introduced in the early 1980s.

Regardless of the cohort to which offenders belong, criminal careers start at age 14, the minimum age for criminal liability in Italy, and end at age 50. This age span balances the inclusion of relevant information for offenders who reached age 50 by the end of the observation period, and the structural unavailability of information on late stages of the criminal career for younger offenders. These data treatment operations led to a subsample of 9819 offenders (9646 males and 173 females, this last group representing only 1.8% of the subsample) and 156,572 offenses. The earliest offense in the data set was committed in 1964 and the most recent one in 2016, thus covering a time frame of 52 years. In this research, crimes are coded as "violent" if they fall under one of these crime categories: assault and violent offenses, murder, and robbery.

A discrete-time Markov process to study violence transitions

We use a longitudinal discrete-time framework to study violent behavior dynamics and the role of co-offending. This is a consequence of the structure of the data set, which provides yearly information on offending. Technically, we reshaped the data on the offending histories of individuals into a longitudinal sequence of criminal "states". Each state describes the offending behavior of a given offender in each year.[4] The main methodological obstacle is that some offenders committed multiple crimes in the same year. Due to the lack of information on the exact date of each crime, it is impossible to order the crimes in the same year. We constructed five mutually exclusive states with the aim of preserving most of the information in the data, while at the same time giving prominence to co-offending dynamics (see Table 1)[5]: the "Violent co-offending" state applies to years in which the offender committed at least one violent offense in cooperation with others, regardless of the cooperative nature and type of other crimes. "Violent solo offending" identifies years with only solo violent offenses (and no violent co-offending, while they may have committed other crime types with or without the company of others). For years with no violent offending, "Co-offending (no violence)" describes states with at least one co-offense (regardless of the cooperative nature of the other crimes), "Solo offending (no violence)" describes states with only solo offenses, and "No crime" are years without offenses.[6] In

[4] We use a categorical description of offending behavior rather than focusing on the number of offenses of a certain type committed each year (even though the data set provides this information). This is because we are theoretically interested in the impact of the *quality* of committed violence each year (whether it is group rather than lone violence), rather than of the *quantity* of violent crimes committed, also considering that in the majority of cases, offenders engaging in violence commit one violent offense per year.

[5] In the definition of the states, we disregarded incapacitation periods (i.e., years in which offenders were incarcerated). While incarceration shows some incapacitation effects on offenders (in the data, about 90% of the total years spent in prison are crime free, in contrast with about 80% of the years spent out of prison), we favored the inclusion of crimes committed in prison over the evaluation of incapacitation effects. Indeed, offenders were convicted for crimes while imprisoned, comprising offences committed in prison (e.g., evasion, or threats to guardians), or offences they have instigated (e.g., a mafia boss commissioning a murder from prison). Evidence from qualitative studies shows that the practice of managing the mafia business from their prison cell (which includes the instigation to commit certain crimes) is far from uncommon for mafia leaders (e.g., Arlacchi 1992).

[6] Our approach to defining states privileges the retention of information on co-offending, rather than creating additional state categories that define years in which the individual committed both solo and co-offenses. We follow this approach to avoid a proliferation of the possible states, which would complicate the

Table 1 Criminal state categories

State	N	% (Across all states)	% (Considering only states with offending, i.e., excluding "no crime" states)
No crime	272,301	81.72	
Solo offending (no violence)	19,584	5.88	32.15
Co-offending (no violence)	29,487	8.85	48.41
Violent solo offending	2494	0.75	4.09
Violent co-offending	9349	2.81	15.35
Total	333,215	100	100

The reported states are mutually exclusive. "No crime" refers to years without offending; "Solo offending (no violence)" describes states with only non-violent solo offenses; "Co-offending (no violence)" describes states with at least one non-violent co-offense (regardless of the cooperative nature of the other crimes); "Violent solo offending" identifies years with only solo violent offenses (and no violent co-offending, while the offender may have committed other crime types with or without the company of others); "Violent co-offending" applies to years in which the offender committed at least one violent offense in cooperation with others, regardless of the cooperative nature and type of other crimes

some analyses, we consider the "Violence" state which merges the "Violent co-offending" and the "Violent solo offending" ones. This data reshaping process led to a total of 333,215 states that describe the yearly offending behavior of the 9,819 mafia offenders between age 14 and age 50. However, the resulting data set is not a balanced panel as the PMM data set reports whether the offender died while imprisoned, in which case they drop out of the final sample. Of the total of 333,215 states, 60,914 (18.28%) are defined as "offending" states, meaning that the offender committed at least one crime in that year.

Our approach focuses on the time dependency of offending behavior and is based upon the principles of a discrete-time Markov process. The key idea is that offending events at time t can impact offending behavior at time $t+1$, $t+2$, and so on (depending on the order of the Markov process). In previous criminological research, Markov models have been applied primarily to study criminal career specialization (e.g., Lattimore et al. 1994; Stander et al. 1989; Wolfgang et al. 1972), as well as recidivism, desistance from crime, and more generally transitions in offending behavior (e.g., Bijleveld and Mooijaart 2003; Loughran et al. 2017; Merlone et al. 2016; O'Brien et al. 2022; Pettiway et al. 1994). To the best of our knowledge, none of these studies focused on the lingering effect of past criminal behavior (especially co-offending) over future violence.

Formally, let t denote the crime number ($t_N = 1, 2, \ldots, 24$), and the set $\{Y_0, Y_1, Y_2, \ldots\}$ the offending sequence, where $Y_t = i_t$ is the criminal state at time t, and its realization i_t can take the values defined in Table 1. The basic property of a Markov chain (called the *Markov property*) is that offending behavior at time $t+1$ is determined only by offending behavior at time t:

$$P\left(Y_{t+1} = j | Y_t = i_t, Y_{t-1} = i_{t-1}, \ldots, Y_0 = i_0\right) = P\left(Y_{t+1} = j | Y_t = i_t\right) = p_{ij} \quad (1)$$

Footnote 6 (continued)

interpretation of transition probabilities, and also in consideration of the low frequency of states with both types of offending (e.g., states in which the individual engages in both violent co-offending and violent solo offending represent only the 1.19% of the total number of violent states).

where p_{ij} is defined as the *transition probability*. Sequential processes may not satisfy the Markov property if transition probabilities are affected not only by the current state, but also by states further in the past. The number of prior states on which the final state depends is the *order* of the Markov process. A Markov chain X_t is of order r, $r = \{1, 2, 3, ...\}$, if:

$$P\left(Y_{t+1} = j | Y_t = i_t, Y_{t-1} = i_{t-1}, \dots, Y_{t-r} = i_{t-r}, ...\right) = P\left(Y_{t+1} = j | Y_t = i_t, \dots, Y_{t-r} = i_{t-r}\right) \tag{2}$$

The order of the Markov chain reflects the memory (i.e., the persistence) of the underlying process.

Dynamic random-effects probit models

We extend the Markov chain framework by relying on dynamic random-effects probit models. The key principle behind these econometric models is the same of Markov models: we allow offending behavior at time t to impact offending events at time $t + 1$ and $t + 2$. However, by relying on these models we are able to quantify the impact of prior offending events by accounting for different confounders and unobserved individual-level effects, i.e., considering that each offender may have a specific tendency to both co-offend and engage in violence that needs to be accounted for when estimating transition probabilities. In dynamic panel models, the within estimator is inconsistent: previous lags of the dependent variable are a function of the residuals of the model, which makes these predictors not strictly exogenous (Hsiao 2003; Wooldridge 2010). In linear models, this issue is solved through appropriate transformations—e.g., transforming the model in first differences to eliminate the unobserved individual heterogeneity (Anderson and Hsiao 1982; Arellano and Bond 1991; Blundell and Bond 1998; Wooldridge 2005). Such transformations are unsuitable for nonlinear models (Wooldridge 2005), as in our case: our dependent variable is indeed a dummy for committing a violent offense at time t (y^V_{it}). This leads to the *initial conditions problem* (Heckman 1981; Hsiao 2003; Wooldridge 2005): individual effects could be accounted for by including the initial condition of the process in the model (y_{i0}) and assuming its independence from unobserved heterogeneity—a strong and often unrealistic assumption.

We address the initial condition problem following Woolridge (2005), who models the distribution of $y_{it}, t_i = 2, \dots, T_i$ conditioning on the set of explanatory variables and on y_{i0}. The key intuition is that differences in longitudinal averaged characteristics are informative about the underlying individual-specific effects, hence the individual-specific component is now more likely to be independent of observed characteristics (Cappellari and Jenkins 2008). We choose to include the within-unit averages of the explanatory variables rather than the values they assume at each t, thus working with a more parsimonious specification. As suggested by Rabe-Hesketh and Skrondal (2013), we also include the initial-period explanatory variables to avoid the possible bias in coefficient estimates caused by the computation of within-means of time varying variables in short panels. While dynamic random-effects probit models found a few applications in economics and finance (e.g., Alessie et al. 2004; Stewart 2007), to the best of our knowledge their application to criminological topics is limited to the study of Witte and Tauchen (2000), which explores the impact of employment on the probability to engage in crime. Our work extends the previous application of these models within criminology by considering additional lags of the dependent variable.

Our first specification of the model is:

$$y_{it}^V = \rho X_i^V + \gamma Z_{it} + \theta t + a_i + u_{it} \tag{3}$$

with:

$$Z_{it} = h_{it} + c_{it} \tag{4}$$

where y_{it}^V is the probability that offender i commits a violent offense at time t, Z_{it} is the vector of time-varying and exogenous explanatory variables (including the offender's age h_{it} and the yearly number of crimes committed c_{it}), t is a control for the crime number, a_i is the offender-specific unobserved effect, and u_{it} is the idiosyncratic error term. X_i^V is the categorical variable capturing the four possible combinations of violent offending in $t-1$ and $t-2$:

i. No violent offending in either period (y_{it-1}^V=0, y_{it-2}^V=0);
ii. Violent offending in $t-2$ but not in $t-1$ (y_{it-1}^V=0, y_{it-2}^V=1);
iii. Violent offending in $t-1$ but not in $t-2$ (y_{it-1}^V=1, y_{it-2}^V=0);
iv. Violent offending in both periods (y_{it-1}^V=1, y_{it-2}^V=1).

Three coefficients will be estimated, reporting the probability of the last three events compared to the baseline probability of no violent offending in either $t-1$ or $t-2$.[7]

Following Rabe-Hesketh and Skrondal (2013), the offender-specific effect is modelled as follows:

$$a_i = \beta_0 + \beta_1 y_{i0}^V + \beta_2 \overline{Z}_i + \beta_3 Z_{i0} + \mu_i \tag{5}$$

where y_{i0}^V is the initial value of the violent dummy (i.e., whether the offender started their criminal career with a violent offense), $\overline{Z}_i$ is the vector of the within-individual averages of the included explanatory variables, Z_{i0} is the vector of initial values of the explanatory variables, and μ_i is a normally distributed individual-specific error term. As a consequence, for the considered explanatory variables (the offender's age and the yearly number of crimes committed), the model includes the initial value, the value at time t, and the within-unit average (see Table 2, which reports summary statistics for these variables).[8] Besides assuring the independence between individual effects and observed characteristics, the inclusion of these regressors allows to control for the onset age and the overall tendency to offend, which are known correlates of the inclination to engage in violence.[9]

[7] In the Supplementary Materials, we present also results from models including only one lag of the violent offense variable (i.e., a dummy variable indicating whether the individual engaged in violent offending in $t-1$) to show consistency in results.

[8] As the maximum likelihood estimation for the violent offending process did not converge when the variable expressing the number of crimes committed in t is included in the model, we included instead the number of crimes committed in $t-1$, which allows to control for the tendency to offend in a similar phase of the criminal career. Results including the number of crimes committed in t and the number of crimes committed in $t-1$ were compared for the violent solo offending process (for which the procedure converged in both cases; see model specification in Eq. (8)), showing very similar results in terms of coefficient direction and significance levels.

[9] We considered the option of including the square of the age variable in the model specification to account for the curvilinear relationship between violence and age (see Fig. 1 below). While age squared is statistically significant when included in models without the random-effects component, it becomes not significant

Table 2 Summary statistics of the exogenous explanatory variables

Variable	N	Mean	Std. Dev	Min	Max
Crime number	60,914	4.77	3.41	1	24
Age at crime	60,914	29.28	8.31	14	50
Age at crime (t0)	60,914	20.55	4.98	14	50
Age at crime (Avg)	60,914	29.28	4.94	15	50
N crimes (t-1)	51,138	2.68	3.25	1	104
N crimes (t0)	60,914	2.14	2.06	1	47
N crimes (Avg)	60,914	2.57	1.50	1	25
N offenders	9819				

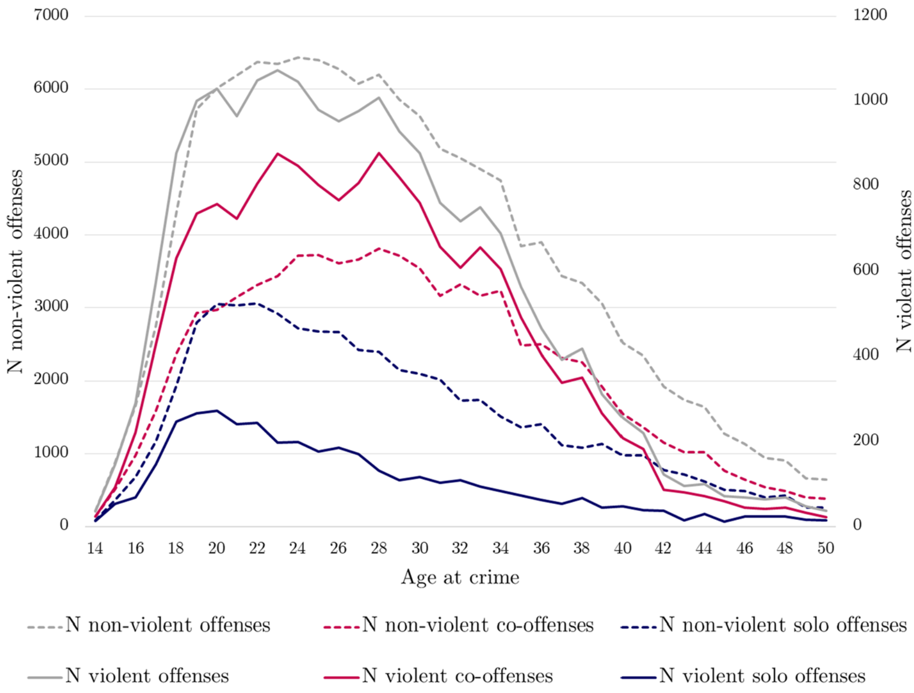

Fig. 1 Number of violent and non-violent offenses, co-offenses, and solo offenses, by age

A second specification of the model extends the one presented in Eq. (3) by decomposing the type of violence committed in previous offending periods (whether it is committed with others or not), allowing for two consecutive periods of the same type of violence:

Footnote 9 (continued)

when the offender-specific effect is added to the model, showing that in this sample the age-violence relationship is linear after accounting for offender-specific effects. We opted to exclude the age squared term from the final models for reasons of parsimony, and considering that results for the other included variables are virtually unchanged regardless of the inclusion of this term.

$$y_{it}^{V} = \varphi X_i^C + \delta X_i^S + \gamma Z_{it} + \delta t + a_i + u_{it} \tag{6}$$

where X_i^C and X_i^S are the categorical variables capturing the four possible combinations of—respectively—violent co-offending and violent solo offending in $t-1$ and $t-2$, in the same way as specified for X_i^V above, and all the other variables are defined as in Eq. (3), (4) and (5).

In a second set of models, we focus on the separate dynamics of violent co-offending and violent solo offending. We consider as dependent variables the dummy for committing a violent co-offense (y_{it}^C) and the dummy for committing a violent solo offense (y_{it}^S) and estimate the state dependence of both violence of the same type and violence of the opposite type committed in the two previous periods:

$$y_{it}^{C} = \varphi X_i^C + \delta X_i^S + \gamma Z_{it} + \delta t + a_i + u_{it} \tag{7}$$

$$y_{it}^{S} = \varphi X_i^C + \delta X_i^S + \gamma Z_{it} + \delta t + a_i + u_{it} \tag{8}$$

Results

We first perform descriptive analyses to examine the longitudinal evolution of solo offending, co-offending, and violence at the aggregate level (Fig. 1 and 2). Co-offenses (cherry-red lines) account for most offenses in the data, also due to the classification choices discussed in the previous section. Their prominence is even more relevant for violent co-offenses compared to violent solo offenses (cherry-red solid line vs blue solid line). Both violent and non-violent co-offending peak just before age 30 and then decline, while solo offending peaks earlier in age, especially violent solo offending (around age 18–20; this is clearly visible in Fig. 2). The longitudinal evolution of all types of offending behavior presents some differences when compared to age-crime curve results derived on general offending samples, particularly regarding the consistent number of offenses committed during adulthood. When considering co-offending specifically (both violent and non-violent), we note how the co-offending rate (i.e., the distance of cherry-red lines from the gray lines of total crimes in Fig. 1) remains relatively constant with the age of organized crime offenders, a finding which differs from similar results for general offenders (e.g., Andresen and Felson 2010; Carrington 2002; Reiss 1988; Warr 2002).

Table 3 and Fig. 3 present aggregate results for the probabilities of committing violence, violent co-offending, and violent solo offending, considering different types of offending behavior in the previous offending period. Such results are derived from computing Markov transition probabilities on the entire sample, as outlined in Sect. 4.2. The conditional probabilities of committing violence demonstrate that at the aggregate level any violent offending in t increases the probability of violent offending in $t+1$ (0.334 vs. 0.196). Violent co-offending in t increases the probability of violent offending in $t+1$ more than violent solo offending (0.357 vs. 0.243). However, violent co-offending is about four times more frequent than violent solo offending (unconditional probability 0.156 vs. 0.04), and the two processes are largely independent: prior violent co-offending more than doubles the probability of future violent co-offending (0.321 vs 0.156), while prior violent solo offending only slightly increases it (0.163 vs. 0.156); conversely, prior violent solo offending doubles the probability of future violent solo offending (0.08 vs. 0.04), while prior

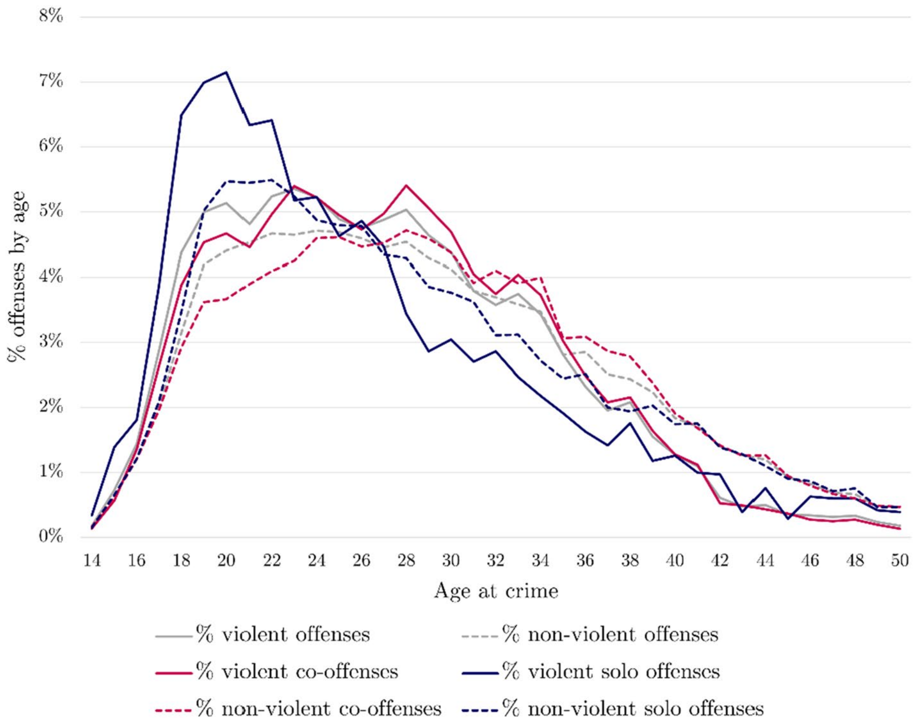

Fig. 2 Number of violent and non-violent offenses, co-offenses, and solo offenses (share by age over total)

Table 3 Probability of committing violence, violent co-offending, and violent solo offending, conditional on different offending events in the prior offending period

Offending event in t	$P(violent_{t+1})$	$P(violent\ co-off_{t+1})$	$P(violent\ solo\ off_{t+1})$	N
Solo offending	0.166	0.118	0.048	19,124
Co-offending	0.214	0.179	0.035	32,014
Violent crime	0.334	0.289	0.045	10,927
Violent solo offending	0.243	0.163	0.080	2227
Violent co-offending	0.357	0.321	0.036	8700
Unconditional	**0.196**	**0.156**	**0.040**	**51,138**

The table presents the aggregate probability of committing violence, violent co-offending, and violent solo offending in $t+1$ conditioning on different offending events in t. The reported events in t are not mutually exclusive (e.g., solo offending includes both violent solo offending and non-violent solo offending)

violent co-offending slightly decreases it (0.036 vs. 0.04). We obtain equivalent results when computing transition probabilities between different years rather than offending periods (i.e., considering the probability of committing violence in t conditional on the offending behavior in the previous *year*); we refer the reader to Table A1 and Figure A1 in the Supplementary Materials for such results.

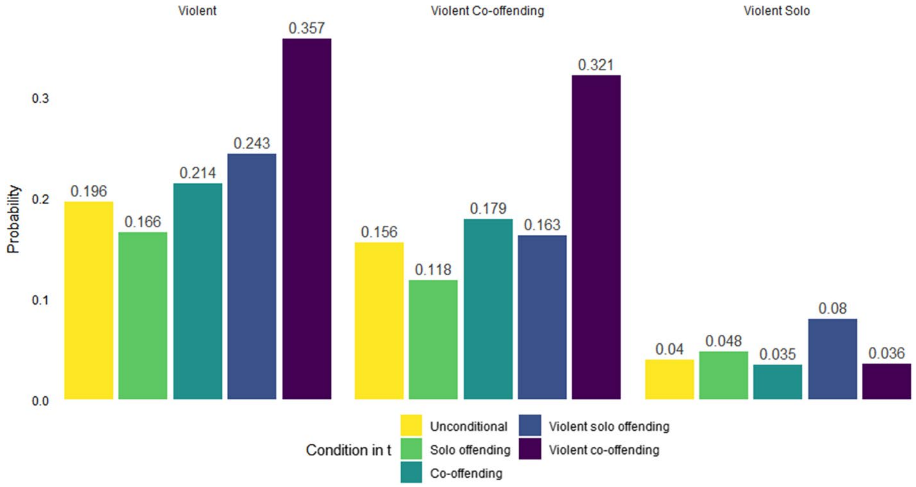

Fig. 3 Probability of committing violence, co-offending violence, and solo offending violence, conditional on different offending events in the prior offending period

As suggested by Fig. 1 and 2, violent solo and co-offending vary over the life course. As other factors beyond age may impact the probability of violence (e.g., the offending frequency, the individual tendency towards violence), we turn to the results of the dynamic random effects probit models to disentangle these effects.[10]

We start by reporting the results of models explaining violence in t by considering distinct types of violent behavior in $t-1$ and $t-2$ (Table 4).[11] Committing any violence in $t-1$ has a positive impact on the probability of violence in t (Table 4, first model). However, considering violent offending in $t-1$ only, violent co-offending has an effect than is nearly three times stronger than violent solo offending (Table 4, second model): the estimated Average Marginal Effect (AME) of committing violent co-offending in $t-1$ only on the probability of violent offending in t is 0.142, meaning that, compared to offenders who did not engage in violent co-offending in $t-1$, those who did are 14.2 percentage points more likely to commit a violent offense in the next period ($SE = 0.008$, $p < 0.001$).

[10] We refer the reader to the Supplementary Materials for results from models including only one lag of the violent offense variable (and symmetric specification otherwise). Results are virtually unchanged in terms of direction and level of significance, with only minor variations in coefficient magnitudes. However, for all specifications, models including two lags of the considered violent offense variables perform better in terms of AIC and BIC values compared to symmetric models including only one lag of these variables.

[11] To validate our model estimates we compared the probability of committing violence in t observed in the sample with the coefficients of the second model reported in Table 4, at different crime numbers and considering different types of violent offending in $t-1$ and $t-2$ (see Table A4 in the Supplementary Materials reporting predicted and observed probabilities up to crime number 8 for reasons of parsimony). As expected, our model performs better when the number of offenders on which the observed value is computed is higher. On average, considering cases in which the number of offenders on which the observed value is computed is higher than 30, the average discrepancy (the difference between observed and predicted probabilities) is 0.039. We also compute a weighted average discrepancy by weighting the absolute differences between predicted and observed probabilities by the number of observed offenders (the last column of Table A4) and averaging out such weighted values. The weighted average discrepancy for the second model reported in Table 4 is 0.015, suggesting that our model performs well when the number of observations on which outcome probabilities are computed is sufficiently high.

Table 4 Dynamic random-effects probit models for the probability of committing violence

	Dependent variable: violence at time *t*			Dependent variable: violence at time *t*		
Variable	β	SE	Sig	β	SE	Sig
Violence (t-1 only)	0.441	0.025	***			
Violence (t-2 only)	0.112	0.024	***			
Violence (both t-1 & t-2)	0.552	0.037	***			
Violent co-offending (t-1 only)				0.499	0.027	***
Violent co-offending (t-2 only)				0.102	0.026	***
Violent co-offending (both t-1 & t-2)				0.639	0.039	***
Violent solo offending (t-1 only)				0.185	0.039	***
Violent solo offending (t-2 only)				0.065	0.037	
Violent solo offending (both t-1 & t-2)				0.354	0.111	**
Violence (t0)	0.112	0.021	***	0.110	0.021	***
Crime number	−0.006	0.004		−0.006	0.004	
Age at crime	−0.025	0.002	***	−0.026	0.002	***
Age at crime (t0)	−0.017	0.003	***	−0.018	0.003	***
Age at crime (Avg)	0.015	0.003	***	0.016	0.003	***
N crimes (t-1)	−0.029	0.003	***	−0.032	0.003	***
N crimes (t0)	−0.035	0.005	***	−0.034	0.005	***
N crimes (Avg)	0.216	0.011	***	0.214	0.011	***
Intercept	−0.779	0.064	***	−0.752	0.064	***
σ_u(offender)	0.028	0.008		0.025	0.008	
Wald Chi-square	χ^2=2281.69, p<0.001			χ^2=2368.73, p<0.001		
AIC	37,521.08			37,452.12		
BIC	37,633.47			37,590.45		
Observations	42,019			42,019		
N of unique offenders	8163			8163		

Notes: ***, **, and * indicate that the estimated coefficient is statistically significant at the 0.1, 1, and 5 per cent level, respectively. Standard errors are clustered at the offender level

Conversely, in comparison to individuals not committing a violent solo offense in $t-1$, those who did are about 4.9 percentage points more likely to engage in violence in the next period (SE = 0.011, $p<0.05$).[12] A violent first offense, earlier onset, and younger age in t also increase the probability of committing future violence.

The effects of prior violence persist beyond the previous period: compared to the baseline of no violence in both $t-1$ and $t-2$, we find a statistically significant and positive effect for any violent offense in $t-2$, although smaller than for violence in $t-1$.

[12] Average Marginal Effects (AMEs) have been computed through the "margins" Stata command, which allows to fix the value of the variable of interest, compute the predicted probability for each case using the observed values for all the other variables, change the value of the fixed variable and compute again the estimated probability, and then obtain the estimated effect as the average of all predicted probabilities (see Williams 2012).

Furthermore, the impact of previous violence is cumulative, as engaging in violence in both previous periods doubles the probability of committing violence. Events in $t-1$ have a stronger effect even in the model unpacking violent co-offending and solo offending in the previous periods, which confirms that previous violent co-offending has stronger impact than prior violent solo offending. Overall, violence is a persistent process with long-lasting effects.[13]

Table 5 examines violent co-offending and violent solo offending probabilities in t. The first model in Table 5 shows that both violent co-offending and violent solo offending in $t-1$ have a positive impact on violent co-offending in t, but the effect of violent co-offending is more than five times stronger. Moreover, any prior violent co-offending positively affects future violent co-offending, with the effect of violent co-offending in $t-1$ only being four times the one of violent co-offending in $t-2$ only; violent co-offending in both previous periods has an even larger effect. The second model in Table 5 shows a positive association between prior violent solo offending in $t-1$ and both $t-1$ and $t-2$ and future violent solo offending. Violent co-offending lacks statistically significant effects on violent solo offending in the next period, except for the negative impact of violent co-offending committed in both $t-1$ and $t-2$. Other individual-level factors produce results consistent with previous models.

Discussion and conclusions

Our findings show that violence is a persistent and long-lasting behavior. We found that the effect of prior violent co-offending on the probability of future violence is greater than the one of prior violent solo offending. Furthermore, while both prior violent solo and co-offending increase the probability of future violent co-offending, only prior violent solo offending enhances the likelihood of future solo violence.

We found support for our first four hypotheses, and namely: (1) Violent offending is persistent (Table 4, first model); (2) Violent offending is long lasting (Table 4, first model); (3) These two results hold also when considering violent co-offending and solo offending

[13] To exemplify our results, we provide the probability to commit violence for three representative offenders, given the type of offending they engaged in during previous offending periods. Offender A has both an onset age and a yearly number of committed crimes that reflect the sample's average (21 and 2, respectively). Across their criminal career, their estimated probability to commit violence in any offending period is 0.146; this probability increases to 0.186 if they committed solo violent offending in the previous offending period only, it is 0.233 if they committed solo violent offending in the two previous offending periods, 0.245 if they engaged in violent co-offending in the previous lag only, and 0.289 (more than double compared to the baseline) if they engaged in violent co-offending in both $t-1$ and $t-2$. A late onset and sporadic offender B (whose onset age is 32 and yearly average number of crimes is 1 – the 90th and 10th percentile, respectively, of the onset age and number of crimes distributions) has a baseline probability to commit violence of 0.073. This value increases to 0.100 if they committed solo violent offending in the previous offending period only, it is 0.131 if they committed solo violent offending in the two previous offending periods, 0.137 if they engaged in violent co-offending in the previous lag only, and 0.170 if they engaged in violent co-offending in both $t-1$ and $t-2$. Finally, the baseline probability of committing violence for an early onset and prolific offender C (whose onset age is 16 and yearly average number of crimes is 6—the 10th and 90th percentile, respectively, of the onset age and number of crimes distributions) is 0.287. Our results show that this value increases to 0.346 if they committed solo violent offending in the previous offending period only, it is 0.407 if they committed solo violent offending in the two previous offending periods, 0.425 if they engaged in violent co-offending in the previous lag only, and 0.478 if they engaged in violent co-offending in both $t-1$ and $t-2$.

Table 5 Dynamic random-effects probit models for the probability of violent co-offending and violent solo offending

Variable	Dependent variable: violent co-offending at time *t*			Dependent variable: violent solo offending at time *t*		
	β	SE	Sig	β	SE	Sig
Violent co-offending (t-1 only)	0.576	0.028	***	−0.014	0.039	
Violent co-offending (t-2 only)	0.157	0.028	***	−0.053	0.038	
Violent co-offending (both t-1 & t-2)	0.749	0.041	***	−0.158	0.060	**
Violent solo offending (t-1 only)	0.101	0.041	*	0.220	0.059	***
Violent solo offending (t-2 only)	0.063	0.039		0.062	0.057	
Violent solo offending (both t-1 & t-2)	0.111	0.128		0.451	0.135	***
Violent co-offending (t0)	0.107	0.025	***			
Violent solo offending (t0)				0.103	0.050	*
Crime number	−0.012	0.004	**	0.014	0.006	*
Age at crime	−0.022	0.002	***	−0.022	0.003	***
Age at crime (t0)	−0.012	0.003	***	−0.028	0.005	***
Age at crime (Avg)	0.014	0.003	***	0.010	0.004	*
N crimes (t-1)	−0.032	0.003	***	−0.009	0.004	*
N crimes (t0)	−0.039	0.006	***	0.007	0.006	
N crimes (Avg)	0.221	0.011	***	0.033	0.009	***
Intercept	−1.099	0.066	***	−1.087	0.100	***
σ_u(offender)	0.023	0.009	**	0.072	0.019	***
Wald Chi-square	χ^2=2303.53, p<0.001			χ^2=271.68, p<0.001		
AIC	32,388.84			13,384.94		
BIC	32,527.17			13,523.28		
Observations	42,019			42,019		
N of unique offenders	8163			8163		

***, **, and * indicate that the estimated coefficient is statistically significant at the 0.1, 1, and 5 per cent level, respectively. Standard errors are clustered at the offender level

separately (Table 5); (4) Prior violent co-offending has a greater impact than prior violent solo offending on future violent offending (Table 4, second model). However, the findings fail to support our fifth hypothesis (prior violent co-offending increases the probability of future violent solo offending, see Table 5, second model). Not only did we find no impact of prior violent co-offending, but we also found that violent co-offending committed in two consecutive precedent periods decreases the probability of future violent solo offending (Table 5, second model). We also found evidence of the contrary: prior violent solo-offending increases the probability of future violent co-offending (Table 5, first model).

Our findings are consistent with previous research on the persistent and long-lasting impact of violent offending (Campana and Giovannetti 2020; Hodgins 2007; Niezink and Campana 2022). In our sample, the impact of previous violence is lasting, because it extends to violence in the second subsequent offense, and also cumulative, as two prior periods of violence have a greater impact on the probability to engage in future violence. Furthermore, the results are in line with research arguing that co-offending may trigger violence contagion dynamics (e.g., Campana and Giovannetti 2020; Conway and McCord 2002; Niezink and Campana 2022): co-offending may transmit violence, as criminal interactions with violent co-offenders provide motives and rationalizations for future violence (Akers 1977, 1998; McCord 1997; Sutherland 1947). We show that violent co-offending increases the individual probability to commit future violent offenses, also compared to violent solo offending.

However, our findings fail to support the internalization of violent behavior often associated to contagion dynamics (Campana and Giovannetti 2020; Conway and McCord 2002): according to this idea, following criminal contact with violent offenders, individuals change their role perception in the social environment and internalize motives and incentives to commit violence (Patel et al. 2013). Yet, in our sample, violent co-offending fails to trigger the internalization of violent behavior leading to future solo violence. Instead, it only increases the probability of future violent co-offending. This suggests that, at the individual level, group processes that facilitate violence—e.g., mechanisms of diffusion of responsibility (see McGloin & Piquero 2009; Rowan et al. 2022; Warr 2002) —may exhibit self-sustaining dynamics: violent co-offending stimulates future violent co-offending, while future violent solo offending remains unaffected. In other words, individuals may still need accomplices in subsequent offending to legitimate their violent behavior. Overall, our results may suggest the existence of a mechanism of contagion different from the one operating through internalization of violence. Prior research has already hinted to the presence of alternative mechanisms mediating the relationship between co-offending and future delinquency: for example, Walters (2020) argued that co-offending leads to increased moral disengagement (through the observation of co-offenders' behavior), which in turn increases future delinquency. In our case, we hypothesize that the individual's perception that legitimizes the participation in violence (e.g., diffusion of responsibility and/or moral disengagement) remains dependent on the presence of accomplices in the criminal act. Van Ham and colleagues (2021) discussed the "persistence in collective violence offending" when examining the behavior of a subset of offenders participating in hooliganism, riots or group fights and persistently engaging in group violence in subsequent offending periods. While our analysis focuses on a very different offending sample, we also find that collective violence shows a persistent feature rather than leading to internalization and solo violent offending.

The relevant need for accomplices in future violent offending may be due to the specificity of our sample, where many violent crimes were likely committed in the context of criminal organizations. As such, organized crime offenders may engage in certain types of violent crimes that require the cooperation of multiple offenders, similarly to other crimes committed by organized criminal groups, such as extortions and trafficking offenses. The role that co-offending plays within organized crime groups opens up context-specific interpretation of our results. Mafia groups provide a favorable social environment for differential association and social learning processes—frequent and repeated interactions facilitate the transmission of techniques, motives, and rationalizations for violence. Yet, these contexts facilitate and encourage cooperative forms of violence, encompassing both violent crimes simultaneously committed by several individuals and violence instigated or ordered by criminal leaders. Joining a mafia impacts the individual's social status and self-perception (Paoli 2003; Lo Verso and Lo Coco 2004) and triggers criminally-relevant obligations and relations. These may include the commitment to engage in collective violence, as one instrument within a broader framework of signals and codes. Violent co-offending in this context is marked by rational and strategic considerations, and this deliberate approach may account for the absence of a contagion effect in subsequent solo violent offenses (Campana and Varese 2013; Dugato et al. 2020; Gambetta 1993). These dynamics are independent from the characteristics of individual co-offenders—a detail that is missing in our data—and associated with broader social and contextual factors. This is consistent with prior research on the impact of membership to other types of criminal groups on future offending and violence. For example, studies have highlighted how gang membership facilitates general and violent offending (Densley 2013; Jütersonke et al. 2009; Klein et al. 2006; Pyrooz et al. 2016). A recent study by Bright and colleagues (2023) has highlighted how affiliation with an Outlaw Motorcycle Gang provides opportunities to develop enduring co-offending relationships, as offenders tended to repeatedly co-offend with the same partners. Walters (2019) showed that gang affiliation increases delinquency in future offending periods and that the effect of the gang is independent from the peer influences arising from contact with specific offenders; in other words, *present* gang affiliation exerts an impact on the individual's *future* decision to offend that is independent from the histories of delinquency of the single gang members. A "collective peer influence" provides youth with attitudes and techniques conducive to crime (Walters 2019, p. 1059). Overall, while street gangs and organized crime groups present important differences, being part of some form of criminal association may favor a persistent, dynamic diffusion or responsibility, incentivizing the future commission of violent crimes in cooperation with others. This mechanism would complement individual facilitation effects of offending behavior observed in prior research.

Our work contributes to the literature on collective behavior and violence transmission both theoretically and methodologically. From a theoretical perspective, we extend previous results on the static impact of collective behavior *during* violent offending by postulating that such impact may exhibit a persistent feature and extend to *future* violent offending. From a methodological perspective, the novel contribution of our analysis is the operationalization of the relation between solo/co-offending and violence as a stepwise process, allowing to examine their interactions at various moments of the criminal career and not between two—potentially discretionary—time windows. Our research is among the few in criminology to utilize dynamic random-effects probit models and is the first to apply them to the dynamics of violence.

Our study presents some limitations. First, our data set comprises official conviction data, which may underestimate the volume of crimes and raise the concern of selective enforcement bias known as the "group hazard hypothesis" (Erickson 1971). However, co-offending research frequently employs official records (Carrington 2002, 2009; McGloin et al. 2008; Sarnecki 2001) and empirical studies did not support the group hazard hypothesis (Feyerherm 1980; van Mastrigt 2008). Second, our co-offending measure is based on the broad definition of collaboration in crime in the Italian criminal law. This approach, while common, may affect the interpretation of our results and any comparison with studies relying on different measures of co-offending. Third, while our data set includes comprehensive longitudinal information on all violent and non-violent crimes of organized crime offenders, we lack information to order crimes committed in the same year. This inevitably reduces the data on transitions between the different offending states and forces to make methodological choices to aggregate the information on crimes committed in the same year. Fourth, we lack information on co-offenders' identities which would permit to include co-offenders' features in the analysis and directly test the violence contagion hypothesis. We also lack data allowing to link (co-)offenders with any potential victim of the offense, thus preventing us from including the impact of violent victimization in the analysis.

To advance the study of co-offending and violence persistence, future research should integrate information on criminal collaboration and co-offenders' characteristics and use granular temporal data. This will enable a better understanding of the mechanisms of violence contagion and whether they depend on the interaction with specific co-offenders or on contextual and social dynamics promoted by group settings. While an increasing number of studies is conceptualizing violence by referring to the captivating concept of a "socially infectious disease", empirical evidence is needed to clarify the specific social and psychological mechanisms driving violence transmission. In this regard, future research may assess whether organized crime membership moderates or prevents the contagion from prior violent co-offending to future violent solo offending. Despite these outstanding issues, our work highlights the importance of examining the relational component of violence—especially from a longitudinal perspective—in addition to individual and ecological determinants. From a prevention perspective, our results suggest that efforts to prevent involvement in violence should also disrupt the group dynamics that promote violent offending.

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Declarations

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