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Parolee Concentration, Parolee Embeddedness, and the Reciprocal Relationship with Crime Rates: A Longitudinal Study of Neighborhoods and Reentry

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Running Head: "Returning Parolees and Neighborhood Crime"

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Bio

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Abstract

Drawing on recent scholarship on mass incarceration and prisoner reentry, this study examines the reciprocal relationship between returning parolees and neighborhood crime rates in five large cities in Texas. Besides the more common approach of counting the number of people on parole in communities (parolee concentration), we propose a novel approach for measuring people on parole by capturing their exposure in the community as *parolee embeddedness* (i.e., the cumulative number of days that people on parole resided in the neighborhood). Results show that parolee concentration has a significant positive effect on both violent and property crime, but parolee embeddedness is significantly associated with *reductions* in violent and property crime. Our findings detect different effects depending on the measurement of people on parole and their community context, illustrating the need to better understand the dynamics of parolee reentry in the era of mass incarceration.

Keywords*: embeddedness, people on parole; neighborhood crime; prisoner reentry*

Parolee Concentration, Parolee Embeddedness, and the Reciprocal Relationship with Crime Rates: A Longitudinal Study of Neighborhoods and Reentry

The process of leaving prison and returning to free society on parole is a long-standing interest among criminologists and sociologists (Clear, Rose, & Ryder, 2001; Clear, Waring, & Scully, 2005; La Vigne & Parthasarathy, 2005; Petersilia, 2003; Visher & Travis, 2003), particularly in the modern era of mass incarceration (Garland, 2001). A consequence of mass incarceration is the unprecedented numbers of formerly incarcerated people returning to society. As of 2016, an estimated 4.5 million adults, or approximately 1 in 55 adults, are under community supervision, in which 874,800 or 13.2% of the total U.S. correctional population are on parole (Kaeble & Cowhig, 2016). With the past four decades showing a dramatic increase in people returning to their neighborhoods on parole, there is a need for research to better understand the neighborhood patterns and consequences of parole for crime.

People on parole are likely to return to a relatively small number of spatially concentrated neighborhoods (Kearns et al, 2018; Kirk 2015), are primarily in impoverished urban areas (Cadora, Swartz, & Gordon, 2003; Kirk, 2015), have many health related issues (Baer et al., 2006), and have limited employment prospects (Boessen & Hipp, 2021; Visher, Debus-Sherrill, & Yahner, 2011). One potential consequence of these patterns is that people coming back into communities may increase neighborhood crime through recidivism (Hipp, Petersilia, & Turner, 2010). Other research, however, documents that when people on parole go back to a community, it can be beneficial for the neighborhood in a variety of ways, including family reunification (Braman, 2007), increasing informal social control in neighborhoods (Hipp & Yates, 2009), and improving economic prospects for families (Braman, 2007). These factors suggest parolee reentry may reduce crime in the neighborhoods they are rejoining. Taken as a whole, the consequences of parole for crime patterns are unclear.

Whereas most existing research focuses on parolee concentration – i.e., the number of people on parole returning to a neighborhood – a key contribution of our study is to consider the temporal aspects of people on parole's exposure to neighborhoods, or what we call *parolee embeddedness*. Parolee embeddedness in neighborhoods involves the extent to which people on parole become integrated or (re)connected within the communities where they live. This approach is rooted in Granovetter's concept of "social embeddedness", which is the idea that economic behavior and institutions are heavily influenced by ongoing social relations (Granovetter, 1985). One aspect of embeddedness encompasses a person's immersion in the social environment with social relations, sense of belonging, and stability (Singh, Shaffer, & Selvarajan, 2018). An alternative perspective on the embeddedness of people on parole considers the duration of their stay in the neighborhood, and this is the current study's focus. Our approach is distinct from nearly all prior quantitative research that focuses on the concentration of people on parole by measuring the number (or rate) of people on parole in a neighborhood when examining the consequences of reintegration for crime or other outcomes; however, a limitation of this common approach is that it does not capture how long people on parole are in the neighborhood. Given that many positive effects of being in a neighborhood likely require a certain degree of neighborhood embeddedness, we consider both where and for *how long* they stay in the neighborhood, instead of simply asking where they return. We propose using the average cumulative number of days people on parole reside in the neighborhood to capture this potential embeddedness and assess whether it affects crime beyond the concentration of people on parole in the neighborhood.

This study uses a longitudinal study design to examine the relationship between parolee concentration, parolee embeddedness, and neighborhood crime. We use data of all people released on parole to neighborhoods in the five largest cities of the state of Texas from 2003 to 2011: Austin, Dallas, Fort Worth, Houston, and San Antonio. As of the 2010 Census, these cities represent 5 of the top 13 largest cities by population in the United States. As the second largest state in the United States by area and population, Texas is also among the top states for number of people on parole. By the end of year 2016, there were 111,287 people on parole in Texas, which is the highest parolee population across states (Kaeble, 2018). Whether returning parolees affect neighborhood crime and vice versa is a crucial empirical question for researchers and policymakers, along with the role of parolee embeddedness in these processes.

People on Parole and Neighborhood Crime

The Impact of People on Parole for Neighborhood Crime

The most direct way that people on parole can impact neighborhood crime is through recidivism. Numerous studies have shown that people on parole often do not successfully complete parole (Alper, Durose, & Markman, 2018; Durose, Cooper, & Snyder, 2014). For example, in one study about 4 in 9 (44%) of released prisoners were arrested during the first year following release and about 2/3 of the prisoners were rearrested within 3 years (Alper et al., 2018). One possibility is that this implies more offending, as shown in prior research that focuses on concentrated parole reentry leading to greater recidivism (Chamberlain & Wallace, 2016). Another possibility is that the concentration of people on parole in a community may attract considerable surveillance from criminal justice agents (Seiter & Kadela, 2003), thereby increasing the probability of coming to police attention, resulting in increased chances of being arrested. This pattern might also imply that many people who experienced prison were not helped by their incarceration. This experience of incarceration did not prepare them for reentry and likely created additional challenges for these individuals and their communities (e.g., see the literature on collateral consequences: National Research Council 2014). The implication is that it is not surprising that recidivism is a challenge post incarceration, and that recidivism contributes to neighborhood crime rates. Therefore, when more people return to a neighborhood on parole, it will likely increase the level of crime (Chamberlain, 2016; Hipp & Yates, 2009; Kovandzic, Marvell, Vieraitis, & Moody, 2004; Livingston, Galster, Kearns, & Bannister, 2014; Raphael & Stoll, 2004).

Another possibility for why neighborhoods with more people on parole might experience higher crime rates stems from the instability associated with the spatially concentrated cycling of people in and out of prison, as well as high rates of residential mobility. Although there is debate about how much residential instability is actually experienced by people on parole—with some scholars finding high levels of mobility (Harding, Morenoff, & Herbert, 2013) whereas others do not (La Vigne & Parthasarathy, 2005; Simes, 2019)—they likely experience more residential mobility than residents more generally. For example, people on parole have limited job prospects upon their return from prison (Boessen & Hipp, 2021), and they usually face financial hardship due to high levels of debt from legal expenses (Drakulich, Crutchfield, Matsueda, & Rose, 2012). As a result, families also bear a substantial economic burden, but seeking assistance can be challenging. From this perspective, there is reason to suspect that people on parole generally do not remain in a single location for an extended period to establish a stable residence, especially given limited help from families, social ties, or society (Seiter & Kadela, 2003).

As another form of instability, incarceration results in some residents being forcibly removed from their communities to prisons or jails, while others are released back into their communities, and this process is conceptualized as "coercive mobility" (Clear et al., 2001; 2003; Rose & Clear, 1998). This frequent mobility of people on parole presumably reduces informal social control in neighborhoods, which in turn can lead to more recidivism and neighborhood crime (Drakulich et al., 2012; Hipp et al., 2010). For example, Drakulich et al. (2012) found that high concentrations of returning prisoners are associated with a reduced capacity for collective efficacy and higher levels of violent crime. Similarly, a study in Tallahassee, Florida found strong evidence that prison cycling has a positive effect on crime in marginalized neighborhoods, which largely supports the coercive mobility theory (Dhondt, 2012). Thus, a community with many residents cycling in and out of prison impedes neighborhood stability, and also feeds back into higher crime rates (Rose & Clear, 1998).

Most studies use cross-sectional data to study whether crime is more likely to occur in places with larger numbers of people on parole, and only a smaller body of literature has studied people on parole and crime in neighborhoods in longitudinal designs (Chamberlain, 2016; Hipp & Yates, 2009). A typical strategy measures the number of people on parole released to the neighborhood over some time period, often annually. However, due to high mobility (Clear, et al., 2003) and high recidivism rates (Alper et al., 2018), simply counting the number of people on parole may not accurately capture the degree of neighborhood exposure, especially for studies using longitudinal annual data.

Failing to account for how long people on parole reside in the neighborhood results in an imprecise assessment of parolee impact (see also work on mobility and environmental exposure: Browning et al., 2017; 2021; Wikström, 2006). The one study of which we are aware that has addressed this issue was by Chamberlain (2016) who created a measure of the number of days each person on parole spent in the neighborhood during the year, rather than the simple count of people on parole. Thus, instead of assuming that each person on parole equally "impacts" a neighborhood, she weighted them by time of exposure. Her strategy addressed this methodological challenge by creating a measure of the number of days of exposure (regardless of the number of people on parole). However, she did not explicitly account for the number of people on parole in the neighborhood. Therefore, her measure confounds the number of people on parole and the number of days they spend in the neighborhood, which is an important distinction given our conceptual argument. In our study, we propose this conceptual idea of embeddedness and how this would affect or be affected by neighborhood crime. Our measure is computed as the average cumulative number of days that parolees spend in the neighborhood, while also accounting for parolee concentration. Thus, the present study is not a replication of Chamberlain (2016)'s work in Ohio, rather, our study highlights the conceptual distinction of parolee measures, and helps to move the field forward by considering how people on parole are affecting the neighborhood based on their exposure in the neighborhood.

Parolee Embeddedness in Neighborhoods

People on parole with longer exposure to the neighborhood are more likely to build social networks and receive support from families and friends. Thus, people on parole who stay in the neighborhood longer are more likely to be embedded in their community and their embeddedness within it might strengthen families, their social networks, access to resources, and social support (Braman 2007, Hipp & Yates, 2009). This parolee embeddedness might impact the neighborhood through changes in informal social control, involvement in community organizations, increased communal solidarity, and neighboring interactions (Lynch & Sabol, 2004). Nonetheless, it is challenging for people on parole to engage with communities when their presence is transient and of short duration.

As an example, consider a neighborhood with 20 people on parole in a year, but these people on parole rapidly commit crimes and return to prison. As a result, these people on parole therefore do not spend much time in the neighborhood. Consider another neighborhood that also has 20 people on parole return in that year, but these persons all spend the entire year in that neighborhood. Do the people on parole affect these two neighborhoods in the same way? Do they contribute to neighborhood crime similarly even if they stay in the neighborhood for different lengths of time? The answer would be most likely no. As evident in the coercive mobility process, an increasing number of people on parole face abrupt removal from their neighborhoods and are sent back to prison, whether due to parole violations or heightened supervision. One consequence is the heightened level of neighborhood instability, which is more likely to lead to adverse neighborhood effects, including increased crime and neighborhood unsafety, as compared to a scenario where the same number of people on parole remain in the neighborhood for a longer duration. The difference could simply be due to the length of exposure in the neighborhood or could capture conceptual differences if the persons in the second neighborhood are better able to adjust to life on the outside and therefore contribute to the neighborhood context through their embeddedness.

For these reasons, we propose an alternative approach for measuring people on parole that supplements the traditional measure of counting the number of people on parole: the cumulative number of days people on parole are present in the neighborhood. We refer to this as *parolee embeddedness*. Thus, whereas existing ecological studies of neighborhoods measure residential population concentration and residential stability (i.e., based on length of residence), under the presumption that these capture criminal opportunities and informal social control capability, respectively, we view parolee concentration and parolee embeddedness measures analogously, except focused on a particular subpopulation.

An advantage of our parolee embeddedness measure is that it may capture the effect of non-recidivating people on parole who stay in the neighborhood longer. The longer duration in the neighborhood to some extent signals that people on parole are better able to adjust to life on the outside. For example, due to coercive mobility, people on parole returning to the community may have more fragmented social networks and concentrate in the same communities, thereby decreasing the resources and services available for reintegration (Fagan, West, & Hollan, 2002). This concentration of people on parole may therefore increase the chances of recidivism (Chamberlain & Wallace, 2016; Stahler et al., 2013). In contrast, parolee embeddedness – people on parole who are embedded in the neighborhood longer – may indicate reuniting supportive relationships that create more cohesion, which could result in less neighborhood crime. Whereas work on coercive mobility typically uses the number of people on parole to capture churning (Chamberlain, 2016; Hipp & Yates, 2009), it may be that the cumulative length of time in the community is more important. Even though we claim that people who stay longer in the neighborhood are better embedded, the operationalization of our parolee embeddedness measure is still a proxy for the connections that one can have when living in a neighborhood longer. As such, we argue that time spent in the neighborhood may be a conceptually interesting process to measure because it captures embeddedness in the neighborhood, to some extent.[1] Thus, to better capture embeddedness we utilize the novel measure of cumulative number of days people on parole live in the neighborhood. We assess whether this measure better explains the parolee-crime association through our analyses while controlling for parolee concentration.

Non-Linear Effect of People on Parole

The consequences of parolee concentration and parolee embeddedness for neighborhood crime are likely nonlinear. Regarding parolee concentration, one possibility considers the consistent evidence of greater concentration being associated with more neighborhood crime. A nonlinear possibility suggests diminishing returns. At smaller concentrations the people on parole in a neighborhood may have an association with more crime, but as the size of this parolee

[1] We acknowledge that although the parolee embeddedness measure directly captures the time people on parole stay in a neighborhood, and more time may mean more embeddedness, we cannot directly capture the strength of connections or actual embeddedness of people on parole.

concentration increases, this positive relationship may diminish as the neighborhood accumulates more social and human capital, strengthening the community's ability and efficacy to self-regulate. The implication is a nonlinear relationship between parolee concentration and neighborhood crime.

Likewise, there is reason to expect a nonlinear relationship between parolee embeddedness and crime. Here we expect reductions in crime associated with their initial reintegration where social ties are rekindled upon release, but as people are integrated longer into the community these initial reductions in crime might wane. This implies a nonlinear negative association in which the relationship between embeddedness and crime flattens out at higher levels. Accordingly, crime may decrease due to the immediate effect of this group's initial adjustment to their reintegration, but as people on parole become more embedded in their communities, their beneficial effect on crime may flatten out. This is because this embeddedness is expected to increase social ties and cohesion in the neighborhood initially, but at some point, there is less ability to add additional social ties as one stays longer in the neighborhood. Thus, we hypothesize a decreasing negative relationship between parolee embeddedness and neighborhood crime.

Whereas parolee concentration and parolee embeddedness likely independently impact neighborhood crime, there are theoretical reasons to expect that they may multiplicatively interact with one another in their relationships with crime. Whereas the literature has consistently documented that neighborhoods with more people on parole are associated with higher crime rates (Chamberlain & Boggess, 2018; Hipp & Yates, 2009), it may be that parolee embeddedness is most important, and most effective, in neighborhoods with greater parolee concentration, possibly due in part to the benefits of agglomeration and longer term parolees' connection to other institutions and people on parole (e.g., at nonprofits). Thus, the cohesion in the neighborhood that parolee embeddedness engenders may be strongest in a neighborhood with a high parolee concentration. This implies an interaction between parolee embeddedness and parolee concentration in which the strongest negative relationship occurs for parolee embeddedness in neighborhoods with high parolee concentration.

The Impact of Neighborhood Crime on Parolee Reentry

In the current study, we use a longitudinal study design to explore our research questions. Although our primary focus is not which neighborhoods people on parole return to, we nonetheless build on work by Chamberlain (2016) and account for this possible endogeneity in our longitudinal models. Whereas Chamberlain (2016) focused on how parolees might impact a broader range of neighborhood factors – including residential instability, vacancies, and economic disadvantage – we focus only on how people on parole impact crime levels but expand the focus by also accounting for our novel measure of parolee embeddedness. A well-known pattern is that people on parole generally return to neighborhoods with similar characteristics as their home neighborhood before prison, and they are likely to be pushed into disadvantaged neighborhoods with high crime rates (Harding et al., 2013). Although people on parole may wish to avoid high crime areas as they likely experience more criminal justice activities in those spaces (i.e., searches of residences, enhanced supervision; Seiter & Kadela, 2003), they likely have limited economic ability to avoid them. A common phenomenon is that people on parole are predominantly concentrated in impoverished urban areas (Cadora et al., 2003; La Vigne, Visher, & Yahner, 2005) and reside in disadvantaged neighborhoods with little support for prisoner reentry (La Vigne, Visher, & Yahner, 2004; Seiter & Kadela, 2003). This push of people on parole into high crime areas is in part about being priced out of other neighborhoods, but also arguably due to the isolation/exclusion of other people outside the neighborhood.

Data and Methodology

Data

The data for this study comes from all people on parole released in Texas from 2003 to 2011. Data were obtained directly from the Texas Department of Criminal Justice (TDCJ). The data provide information on when people started on parole and when they ended. People on parole were followed until the end of their parole (revoked or discharged) or until July 2012, which is the date when the data collection ended. The TDCJ also tracked where people on parole resided after release and we geocoded their home addresses using Google and ArcGIS ArcMap 10.6. Nearly all people on parole reported an address, and about 88% of unique addresses were geocoded to an exact X-Y coordinate and joined to the appropriate census block. These 88% of unique addresses are then matched to the five cities with crime data in Texas in the current study. For crime data, we obtained yearly data from the five largest cities in Texas: Austin, Dallas, Fort Worth, Houston, and San Antonio. Annual crime data cover Part I crimes, and we geocode the addresses of the crime events to X-Y coordinates and aggregate them to census blocks. Overall, the geocoding match rate is quite high, ranging from 97.6% in Houston to 99.3% in San Antonio.

The average number of people released on parole is 14,920 for Austin, 63,737 for Dallas, 36,142 for Fort Worth, 124,611 for Houston, and 44,983 for San Antonio. The percentage of male people on parole is similar for these five cities, but Austin (31.7%) and Fort Worth (30.6%) have the highest percent of white people on parole, Dallas (66.9%) and Houston (64.2%) have the highest percent of Black people on parole, and San Antonio (70.5%) has the highest percent of Latino people on parole. The majority of people on parole fall into the age categories of 35-49 and 50-64 years old, and there is no notable difference between each city. More summary information about the data of those released on parole is shown in Appendix Table A1, including number of people on parole, gender, race, married or not, and different age categories, averaged over the 9-year period.[2]

Existing studies examining prisoner reentry have focused on the state level (Hannon & DeFina, 2014, Kovandzic et al., 2004) or the tract level (Lee, Harding, & Morenoff, 2017). Studies on the parolee-crime relationship at smaller geographic scales have typically used census defined tracts (Kubrin & Stewart, 2006) or block groups (Chamberlain, 2016) to measure neighborhoods. However, a limitation of census-defined geographic units is that they typically do not capture the normal activity space of persons (Golledge & Stimson, 1997). For example, a person living near the boundary of a census-defined unit will typically spend much more time in adjacent units rather than their own tract (Jones & Pebley, 2014), and therefore using census-defined units inappropriately fails to capture these processes. For this reason, the strategy we adopt uses egohoods as our measure of neighborhoods to better take into account the spatial patterns of local daily routine of people on parole (Hipp & Boessen, 2013). Egohoods are built on the insight that the spatial patterns of individuals' social lives tend to exhibit a distance decay function, rather than being confined to their own census defined unit. Further, the egohoods approach captures the spatial patterns of persons' local daily routine activities and how that can give rise to crime in the built and social environment around a small geographic unit. Indeed, Hipp and Boessen (2013) in their study showed that crime in ecological units was much better explained by aggregating typical measures to egohoods rather than census-defined units. For these reasons, we argue that egohoods are a more effective measure of neighborhood for

[2] Although we do not focus on the recidivism rate in our study, it helps understand the population of people on parole in Texas. According to the report from Legislative Budget Boards, *Statewide Criminal and Juvenile Justice Recidivism And Revocation Rates*, February 2015, the recidivism rate in Texas is fairly low, around 21.4 percent of individuals released from prison are returned to prison within three years following release, and this recidivism rate is consistent from 2009 to 2011. Retrieved from: http://www.lbb.state.tx.us/Documents/Publications/Policy_Report/1450_CJ_Statewide_Recidivism.pdf.

understanding the relationship between returning people on parole and neighborhood crime, and better address the modifiable areal unit problem (Openshaw & Taylor, 1981). Thus, the units of analysis in the current study are egohoods in these cities, where an egohood is a census block and all blocks surrounding it within a ¼ mile radius.[3] Overall, there are a total of 86,446 egohoods with crime data in the five largest cities of Texas.

To measure neighborhood characteristics, we combine several datasets with these parole and crime data, and all data are harmonized to egohoods in 2010 census block boundaries. First, we capture business information with *ReferenceUSA* Historical business data from *Infogroup.* Reference USA is an annual dataset that contains geographic information allowing us to locate businesses at the address level each year. Second, as community voluntary organizations may help a neighborhood reintegrate people on parole, we measure the presence of voluntary organizations using annual data come from the National Center for Charitable Statistics (NCCS), which contains information on exempt organizations from the Internal Revenue Service's Business Master File.[4] We geocode these organizations based on their provided address and place them into the appropriate census block.[5] Finally, we use 2000 U.S. census data to capture neighborhood sociodemographic information.

Outcome Measures

Neighborhood Crime Rates. We use crime rates per 10,000 population in a quarter mile egohood per year as our crime measure. Crime events are aggregated into yearly totals for

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[3] All the models are based on ¼ mile egohoods in this study. We also estimated models with ½ mile egohoods, and the patterns of results were very similar. Tables are available upon request.

[4] The organization data extract is downloaded from the NCCS database from the Urban Institute. See "https://nccs-data.urban.org/data.php?ds=bmf" for more information.

[5] About 1/3 of the organizations only have zip code information. For these cases, we uniformly assign the organization to all blocks in the zip code (e.g., if there are 100 blocks, then each block is assigned 1% of an organization). Given the subsequent aggregation to egohoods, this spatial smoothing is not a serious issue for these observations.

violent crime (homicide, robbery, and aggravated assault) and property crime (burglary, larceny, and motor vehicle theft). All crime rate variables are log transformed to account for the skewed distribution.

People on Parole. To examine the relationship between the presence of people on parole returning to the community and neighborhood crime, we compute the number of people on parole (i.e., *parolee concentration,* log transformed, after adding 1, to address the skewed distribution) residing in a particular egohood in a given year. In this measure, anyone who has stayed in the neighborhood in that year, regardless of duration, is counted as one parolee. We also construct a measure of *parolee embeddedness*, the average cumulative parolee days in an egohood until released from parole. This was calculated by taking the cumulative number of days people on parole have resided in a particular egohood based on the start date and end date of people on parole's status and then dividing by the yearly total number of people on parole.[6] The correlation between parolee concentration and parolee embeddedness varies year by year, ranging from 0.38 to 0.57, which does not pose collinearity issues, especially given the large sample size (see O'Brien, 2007) and highlights the conceptual distinctness of these measures. To capture non-linear effects, we include the squared terms of *parolee concentration and parolee embeddedness.* We also compute the interaction between parolee concentration and parolee embeddedness and their quadratic measures.

Exogenous Variables

Socio-demographic Variables. Several measures from the 2000 census are included in the models to capture neighborhood characteristics. For Census measures that are not available in blocks, we first impute them from block groups or tracts to blocks using the synthetic estimation

[6] If people on parole start and end their status as parolee within the same year, then this measure equals the end date subtracting the start date. If the parolee days span multiple years, then days are computed cumulatively since entering the egohood. This cumulative measure increments each year they remain in the neighborhood.

of ecological inference strategy and then construct the egohood measures based on the imputed block values.[7] *Residential stability* is measured with a standardized factor score from a factor analysis. Three variables are combined: average length of residence, percent of households that moved into their residence within the last five years (which loads negatively), and percent homeowners. *Concentrated disadvantage* is also measured as a factor score from a factor analysis using five variables: percent of residents below poverty, percent unemployed, percent single parent households, average home value, and average household income (these last two have negative loadings).[8] Racial/ethnic composition of neighborhoods is measured as *percent Black* and *percent Latino*. We capture the *racial/ethnic heterogeneity* of the neighborhood with a Herfindahl index of five racial/ethnic groups (Asian, Black, Latino, White, and other race). To capture inequality, we use household income to construct the *Gini inequality index*.[9] We also include *percent immigrants* in the neighborhood with a measure of percent foreign born. We construct a measure of young people *(percent individuals aged 16 to 29)* in the egohood. We also control for *population* in the egohood, which is implicitly population density given that egohoods have a constant size.

[7] The synthetic estimation for ecological inference is described by Boessen and Hipp (2015) and imputes values to blocks based on the relationships between variables at the higher geographic unit of analysis (Cohen and Zhang 1988; Steinberg 1979). This relaxes the strict assumption of uniform imputation strategies that there is no relationship between the variables. In this strategy, a model is estimated at the larger geographic unit predicting the variable of interest, and the coefficients obtained from the model are multiplied by the values of the variables at the block level. This yields a predicted value for the variable at the block level. If desired, one can use a multiple imputation strategy with this approach, along with adjusted standard errors. The variables used in the imputation model are: percent owners, racial composition, percent divorced households, percent households with children, percent vacant units, population density, and age structure (percent aged: 0-4, 5-14, 15-19, 20-24, 25-29, 30-44, 45-64, 65 and up, with age 15-19 as the reference category).

[8] We also check the correlation between parolee concentration/embeddedness and neighborhood disadvantage and residential stability. The correlation between parolee concentration and neighborhood disadvantage is around 0.57. The correlation between parolee embeddedness and neighborhood disadvantage is around 0.27, with the highest as 0.36. In contrast, the correlation between parolee concentration/embeddedness and residential stability is quite low, around -0.01 to 0.06.

[9] Given that the data are binned we used the rpme ado package for Stata from von Hippel, Hunter and Drown (2017).

Business and Organization Variables. First, research shows that nearby jobs are a key predictor of people on parole's successful reintegration (Boessen & Hipp, 2021) and prior work also suggests that businesses (i.e., land uses) are key predictors of neighborhood crime (Boessen & Hipp, 2015). Accordingly, we measure the number of 1) total employees in all businesses, 2) retail employees, 3) recreation employees, and 4) food employees, which come from the Reference USA Historical data. We log transform these measures given that this better captures the empirical relationships. Second, voluntary organizations help people on parole reintegrate with the community (Hipp & Yates, 2009), and we measure organizations using data from National Center for Charitable Statistics. Using the National Taxonomy of Exempt Entities (NTEE) codes that are provided by the organizations, we compute the *total service voluntary organizations* (log transformed, after adding 1), and these organizations include mental health services (e.g., mental health treatment, alcohol/drug abuse treatment), crime (e.g., delinquency prevention, crime prevention), care (e.g., rehabilitation services, transitional care), abuse (e.g. spouse abuse, child abuse), legal (e.g., legal services, public interest law), vocational (e.g., training, job procurement assistance), food (e.g., food banks, nutrition programs), recreational (e.g., community recreation centers, recreation clubs), and neighborhood (e.g., block clubs, community coalitions).[10] These organization variables are captured year by year. Note that we are not able to determine which of these organizations provide services specifically to persons on parole, the services they do provide would arguably be of use and importance to such persons.

Analytic Strategy

To account for possible endogeneity between neighborhood crime and people on parole, we employ longitudinal structural equation models (SEM) in our analyses. Specifically, using

[10] The service organizations were classified based on the following NTEE codes: F20, F21, F22, F30, F42, F50, F52, F53, F54, F60, F70, F80, I31, I40, I43, I44, I70, I71, I72, I73, I80, I83, J20, J21, J22, J30, J32, J33, K30, K31, K34, K35, K36, K40, K50, I20, I21, I23, N20, N30, N31, N32, N40, N50, S20, S21, S22.

longitudinal data on neighborhoods, we estimate a series of cross-lagged equation models, a procedure that allows us to account for temporal autocorrelation in the residuals. The models are estimated using city fixed effects (by centering the data by city), and we calculate robust standard errors. Additionally, we constrain the coefficients of the variables to be equal over waves and test the consequences of this constraint for model fit (Hipp, Tita, & Greenbaum, 2009; Hipp & Wickes, 2017). We model one-year lags given that crime responding to parolee reentry likely requires a year to capture the effect. Thus, our model specifies that the presence of people on parole in a prior year affects neighborhood crime in the current year while taking into account the one-year lag of crime and controlling for a variety of additional neighborhood-level factors. We also assess whether crime in the prior year predicts parolee concentration and parolee embeddedness in the next year, while also controlling for the same neighborhood factors. We include all these socio-demographic measures at the year 2003 time point of the 2000 Census.[11] The theoretical model is depicted in Figure 1.

[FIGURE 1 ABOUT HERE]

For each outcome, the cross-lagged models are estimated using the following equations:

$$\mathbf{Crime}_{\mathrm{it}} = \boldsymbol{\beta}_{10t} + \boldsymbol{\beta}_{11t}\mathbf{Crime}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{12t}\mathbf{Concentration\ measures}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{13t}\mathbf{Embeddedness\ measures}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{14t}\mathrm{X}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{15t}\mathrm{Z}_{\mathrm{i}} + \varsigma_{1it} \quad (1)$$

$$\mathbf{Parolee\ concentration}_{\mathrm{it}} = \boldsymbol{\beta}_{20t} + \boldsymbol{\beta}_{21t}\mathbf{Crime\ measures}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{22t}\mathbf{Parolee\ concentration}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{23t}\mathrm{X}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{24t}\mathrm{Z}_{\mathrm{i}} + \varsigma_{2it} \quad (2)$$

$$\mathbf{Parolee\ embeddedness}_{\mathrm{it}} = \boldsymbol{\beta}_{30t} + \boldsymbol{\beta}_{31t}\mathbf{Crime\ measures}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{32t}\mathbf{Parolee\ embeddedness}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{33t}\mathrm{X}_{\mathrm{i(t-1)}} + \boldsymbol{\beta}_{34t}\mathrm{Z}_{\mathrm{i}} + \varsigma_{3it} \quad (3)$$

[11] We linearly interpolated these measures between 2000 and 2010 and used the 2003 values given that they match the first year of the study. Note that we cannot use these interpolated values from multiple years in the analyses as the linear interpolation introduces perfect collinearity. Instead using the 2000 values yielded essentially identical results to those presented here.

where $Crime_{it}$ is the outcome variable of logged neighborhood-level violent (or property) crime rate in year *t*. The outcomes Parolee concentration and Parolee embeddedness are the number (logged) and average days of people on parole for egohood *i* which are measured at time *t*, respectively. In equation (1), $\boldsymbol{\beta}_{10t}$ is the intercept, $\boldsymbol{\beta}_{11t}$ is a vector of parameters that captures the crime measure from the previous time point *(t-1)*, in which we have constrained the effect for different waves to be equal. We include parolee concentration in egohood *i* at time point (*t-1*) with coefficients in the $\boldsymbol{\beta}_{12t}$ vector. We also include parolee embeddedness in egohood *i* at time point (*t-1*) with coefficients in the $\boldsymbol{\beta}_{13t}$ vector. Here, concentration measures include parolee concentration and parolee concentration squared; and embeddedness measures include parolee embeddedness and parolee embeddedness squared. $X_{i(t-1)}$ is a matrix of organization variables and the constrained equal coefficients for different waves are captured in $\boldsymbol{\beta}_{14t}$ vector. Z_i is a matrix of several neighborhood-level socio-demographic variables at the first time point of year 2003 with the accompanying coefficients captured in $\boldsymbol{\beta}_{15t}$ vector, where the coefficients for different waves are also constrained to be equal.[12] Equations (2) and (3) are the ones with parolee concentration and parolee embeddedness as outcomes; we do not have parolee concentration or parolee embeddedness predict each other. Here crime measures include crime and crime squared. Finally, ς_{1it}, ς_{2it} and ς_{3it} are error terms with assumed normal distributions. We account for temporal autocorrelation by estimating covariances between the errors of crime at time *t-1* and time *t*, and those between people on parole at time *t-1* and time *t*. We also estimate the covariances between the errors of crime and the parole measures at the same time point.

We estimate a series of structural equation models (SEM) in Stata 15.0 (StataCorp, College Station, TX) and use full information maximum likelihood (FIML) to handle missing

[12] Note that this approach captures the averaged effect over this time period, as the time lag between these measures and the outcome measure necessarily differs over years.

data (Allison, 2012).[13] Table 1 presents the summary statistics of the variables used in the analyses.

[TABLE 1 ABOUT HERE]

Results

Relationship between Returning Parolees and Crime

To examine the cross-lagged relationship between people on parole and crime, Table 2 presents a series of SEMs with outcome variables of violent/property crime and parolee concentration and parolee embeddedness controlling for a variety of socio-demographic and organization measures. We discuss the result of people on parole's effect on crime – either violent crime or property crime – first, and then discuss effects of neighborhood crime on people on parole. We note that the SEMs show good model fit. For example, in model 1 Table 2, the root mean squared error of approximation (RMSEA) is 0.03, and the comparative fit index (CFI) is 0.95, indicating a good model fit.

[TABLE 2 ABOUT HERE]

Starting with violent neighborhood crime as an outcome, unsurprisingly, the one-year lag of violent crime rates has a strong positive effect on violent crime rates in the following year, indicating considerable stability in the level of crime from year to year. In Model 1 of Table 2, the coefficient of lagged violent crime is 0.865, indicating that a 1% increase in violent crime rates in the prior year is expected to increase violent crime rates in the current year by around 0.87%, holding other variables constant. For ease of interpretation, the nonlinear results of parolee concentration and embeddedness are presented in Figure 2 and Figure 3. Note that in

[13] Although egohoods create spatial overlap, this will have ambiguous impacts on the standard errors. Hipp and Boessen (2013) estimated their models both with and without a spatial error structure and showed that the standard errors were very similar to the non-spatial models. This is a well-known feature of spatial error models. Given the complexity of our models, estimating them with a spatial error term was not possible.

these figures we are plotting parolee concentration or embeddedness from one standard deviation below the mean to one standard deviation above the mean. The fixed effects models center the variables within each city, and therefore the zero value indicates the average level of parolee concentration (or embeddedness) in a particular city, with negative values showing egohoods with below average levels of parolee concentration (or embeddedness). There is a positive relationship between parolee concentration and violent/property crime. Specifically, we used the plotted expected values from the nonlinear relationship to find that for an egohood with no parolee concentration, a one standard deviation increase in parolee concentration is associated with 5.6% more violent crime and 2.3% more property crime the next year; if the egohood had an average parolee concentration level, then a one standard deviation increase is associated with 3.9% more violent crime and 1.1% more property crime the next year. As we can see in Figure 2, the effect of parolee concentration on violent crime is larger than that on property crime. However, in Figure 3 we see that our parolee embeddedness measure yields a different relationship with crime compared to the concentration measure: the cumulative parolee days residing in the egohood in one year has a significant *negative* relationship with both violent and property crime rates the following year. A one standard deviation increase in parolee embeddedness is associated with about a 1-2% decline in violent or property crime.

[FIGURE 2 ABOUT HERE]

[FIGURE 3 ABOUT HERE]

Regarding the control variables, we see that a one standard deviation increase in concentrated disadvantage is associated with 4.4% more violent crime and 1.1% more property crime, a similar increase in residential stability is associated with about 1.1% less violent crime, and a similar increase in racial/ethnic heterogeneity is associated with 1.2% and 0.2% more violent and property crime, respectively. Thus, these measures are of a similar magnitude, or even smaller, than the parolee measures.

Turning to the effect of crime on people on parole, the results in Table 2 also highlight strong evidence that the violent or property crime rate affect parolee concentration the following year, and modestly impact parolee embeddedness. A one standard deviation increase in the violent crime rate in an egohood in one year is associated with an approximately 3.3% increase in the number of people on parole the following year (though this is somewhat weaker at higher violent crime rates). A similar increase in property crime has a smaller effect, resulting in a 1.6% increase in people on parole the following year for neighborhoods increasing from low property crime levels; this effect weakens and reverses at high property crime levels. This suggests that people on parole tend to return to neighborhoods with more neighborhood crime, particularly violent crime. There is only a very modest relationship between violent or property crime and parolee embeddedness.

Other neighborhood characteristics also impact parolee concentration and parolee embeddedness. As expected, a one standard deviation increase in concentrated disadvantage is associated with 2.6% more people on parole in the egohood; however, opposite our expectations, higher concentrated disadvantage results in more parolee embeddedness – about 4 more days, on average, the following year – holding other variables constant. One of the strongest effects is for percent Black in the egohood: however, although a one standard deviation increase is associated with almost 10% more people on parole the following year in such neighborhoods, it is also associated with *greater* parolee embeddedness (about 12 more days spent in the neighborhood, on average, the following year). As expected, greater residential stability in the neighborhood has a relatively strong positive relationship with parolee embeddedness the following year. Furthermore, consistent with the expectation that services attract people on parole as residents, there is evidence that service voluntary organizations in the neighborhood are associated with greater parolee concentration and parolee embeddedness the next year.

Interaction Effects

We also observe a substantial moderating effect of parolee concentration and parolee embeddedness for property crime, but not for violent crime. As shown in Figure 4, the negative relationship between parolee embeddedness and property crime is much stronger in egohoods with greater parolee concentration compared to those with few people on parole. Thus, the combination of people on parole along with parolee embeddedness appears particularly beneficial regarding property crime for neighborhoods with more concentration.

[FIGURE 4 ABOUT HERE]

Sensitivity Analyses

Given that our analyses combined five separate cities, we estimated ancillary models for each city separately to assess the robustness of the results.[14] Among these five cities in Texas, the positive relationship for parolee concentration was present for both violent crime and property crime for all cities with the exception of San Antonio for property crime, which was non-significant. The parolee embeddedness measure showed a consistent nonlinear negative relationship with violent crime for all cities, and for property crime in all cities except Austin. There was also a consistent positive relationship between violent crime rates and where people on parole relocated across these cities. Thus, the pattern of results was generally consistent across these cities, although the nonsignificant relationship between parolee embeddedness and crime in Austin suggests that future research will want to assess this measure across different cities.

[14] Results are available upon request.

Discussion and Conclusion

Although crime rates and prison populations have been mostly on a downward trend over the last decade in the United States, the accumulated prison population is still massive, and there are increasing numbers of people being released back to communities. Moving beyond the traditional measure of parolee concentration, this study considers parolee embeddedness, which is the amount of time people on parole live in the neighborhood after returning from prison. We also test whether there are potential non-linear effects of parolee concentration and parolee embeddedness on neighborhood crime rates in our longitudinal analyses of the five largest cities in Texas. Key findings are discussed below.

Overall, our study provides evidence that parolee concentration contributes to neighborhood crime: a greater number of people on parole living in a neighborhood in one year is associated with higher violent and property crime rates the following year. This finding is in line with a longitudinal study in Sacramento with monthly crime rates (Hipp & Yates, 2009), studies in Cincinnati and Columbus (Chamberlain, 2012) and Cleveland (Chamberlain, 2016; Chamberlain & Boggess, 2018) with annual crime rates, cross-sectional studies in Seattle (Drakulich, et al., 2012), and Multnomah County, Oregon (Kubrin & Stewart, 2006). This body of literature has focused on neighborhoods within cities or counties across different states, including California, Ohio, Michigan, Washington, and Oregon. We also find similar evidence in the five Texas cities captured here – Austin, Dallas, Fort Worth, Houston, and San Antonio. Although some research argues that the impact of prison releases on crime differs across various state-level parole systems (Raphael & Stoll, 2004), our study shows a similar pattern compared to other locations. That said, these effects are relatively small, which may suggest that the considerable attention paid to reentry of people on parole is overblown, particularly in comparison to other issues that communities face.

Nonetheless, a key contribution of this study is introducing a new way to conceptualize the effect of people on parole – the average cumulative number of days that people on parole resided in the neighborhood – and this measure of parolee embeddedness exhibits interesting results. Neighborhoods with people on parole who reside longer in their neighborhood (i.e., longer exposure) experience *lower* violent and property crime rates. This negative relationship suggests that people returning to and staying in the communities might actually help reduce neighborhood crime. It is possible that people on parole who stay in the neighborhood longer are those ex-offenders who have a low recidivism rate. Another possibility is that people on parole who stay in the neighborhood longer are better able to integrate into the community and return to a prosocial life trajectory, which can help enhance social ties in the neighborhood and further decrease neighborhood crime rates (Clear et al., 2003). Still, more research is needed for understanding the dynamic relationship between people on parole and crime.

Future research might not simply examine how long people on parole are embedded into the community, but how various mechanisms of reentry (access to social support networks; changes in the economy, recidivism, access to resources, whether someone was on parole or not, etc.) connect with length of time spent in the neighborhood. While we have shown that being in the community longer is typically associated with lower crime rates, it is not clear why this is occurring. Depending on the mechanism, it is also not always clear that longer is better, and there may be differences in the association between parolee embeddedness and crime. As such, this project has been a necessary first step to using an alternative measure to capture reentry, and future research will want to connect it more explicitly to various mechanisms.

Neighborhood crime rates are not simply affected by only the concentration of people on parole or the embeddedness of this group of people, rather, both concentration and duration matter. We find evidence of a moderating effect in that parolee embeddedness along with larger numbers of people concentrated on parole particularly benefits neighborhoods and resulting in greater reductions in property crime. Accordingly, this pattern indicates that embeddedness is most important in communities that have average or even above average concentrations of people on parole. As such, duration in a hot spot of people on parole suggests that the agglomeration of people, place, and networks of support matter for reducing crime rates and reintegration.

Despite the uniqueness of our data and the importance of our findings, certain limitations deserve to be acknowledged. Although we proposed this novel measure of parolee embeddedness, our measure is primarily a proxy of embeddedness, rather than directly capturing the connections and duration of ties people on parole may have in the neighborhood. Relatedly, while we argued that egohoods better capture the spatial patterns of residents compared to other neighborhood measures, they are not able to perfectly capture social interactions. An additional limitation is that we did not have annual measures of the sociodemographic variables, but simply had cross-sectional measures. Given Chamberlain's (2016) work showing that parolees are pushed into disadvantaged neighborhoods, this is a limitation (Clear, 2009; Morenoff & Harding, 2014). For the present study, people on parole were tracked to their current address after release from prison, however, we do not have information on where people on parole lived before they were sent to prison. Due to this data limitation, we cannot tell whether people on parole cluster in neighborhoods in which they previously lived, or if they geographically disperse. We also emphasize that our approach here is not designed to encourage extending the periods in which people are under parole supervision, but to instead argue that the measurement of reentry is important, and that people need time to readjust to life on the outside.

The findings from this study indicate that when people on parole are in their communities longer, there tends to be some reductions in violent and property crime. As such, one implication is that minor infractions or technical violations of parole that disrupt and often remove people from the community (i.e., a stint in jail or prison) may be counter-productive to helping people reenter into the community. In some ways, this logic is akin to some school discipline policies (i.e., expelling vs. supporting and keeping youth within the school). In other words, polices that suspend or expel people from their community for minor infractions may ultimately hinder people on parole's ability to successfully complete parole because it will likely disrupt their lives and support in considerable ways, and even have negative consequences for the neighborhood.

In closing, our research advances the understanding of prison reentry and neighborhood crime across multiple dimensions. We advance the literature of people on parole and neighborhood crime by introducing a novel concept – *parolee embeddedness* – and examining how the cumulative amount of time people on parole reside in the neighborhood shapes the dynamics of parolee reentry and neighborhood crime in an era of mass incarceration. In addition, we extend previous research on the effect of people on parole on neighborhood crime by also examining the non-linear effect of parolee concentration and parolee embeddedness patterns. Our new approach to measuring people on parole augments the strategy of simply counting the number of people on parole in a neighborhood, and we believe it may provide new insights for researchers interested in neighborhood and parole processes.

References

Allison, P. D. (2012). *Handling missing data by maximum likelihood.* Paper presented at the SAS global forum.

Alper, M., Durose, M. R., & Markman, J. (2018). *2018 update on prisoner recidivism: A 9-year follow-up period (2005-2014)*: US Department of Justice, Office of Justice Programs, Bureau of Justice.

Baer, D., Bhati, A., Brooks, L., Castro, J., La Vigne, N., Mallik-Kane, K., . . . Roman, J. (2006). Understanding the challenges of prisoner reentry: Research findings from the Urban Institute's prisoner reentry portfolio. *Washington, DC: The Urban Institute*.

Boessen, A., & Hipp, J. R. (2015). Close-ups and the scale of ecology: Land uses and the geography of social context and crime. *Criminology, 53*(3), 399-426.

Boessen, A., & Hipp, J. R. (2018). Parks as crime inhibitors or generators: Examining parks and the role of their nearby context. *Social Science Research, 76*, 186-201.

Boessen, A., & Hipp, J. R. (2021). The network of neighborhoods and geographic space: Implications for joblessness while on parole. *Journal of Quantitative Criminology, Forthcoming*.

Braman, D. (2007). *Doing time on the outside: Incarceration and family life in urban America*: University of Michigan Press.

Browning, C. R., Calder, C. A., Boettner, B., & Smith, A. (2017). Ecological networks and urban crime: The structure of shared routine activity locations and neighborhood-level informal control capacity. *Criminology*, 55(4), 754-778.

Browning, C. R., Pinchak, N. P., & Calder, C. A. (2021). Human mobility and crime: Theoretical approaches and novel data collection strategies. *Annual Review of Criminology*, *4*, 99-123.

Cadora, E., Swartz, C., & Gordon, M. (2003). Criminal Justice and Health and Human Services: An Exploration of Overlapping Needs, Resources, and Interests in Brooklyn Neighborhoods (From Prisoners Once Removed: The Impact of Incarceration and Reentry on Children, Families, and Communities, P 285-311, 2003, Jeremy Travis and Michelle Waul, eds.

Chamberlain, A. W. (2012). *Community Change and Recidivism: The Interrelationship Between Neighborhood Ecology and Prisoner Reintegration*: University of California, Irvine.

Chamberlain, A. W. (2016). From Prison to the Community: Assessing the Direct, Reciprocal, and Indirect Effects of Parolees on Neighborhood Structure and Crime. *Crime & Delinquency, 64*(2), 166-200.

Chamberlain, A. W., & Boggess, L. N. (2018). Parolee Concentration, Risk of Recidivism, and the Consequences for Neighborhood Crime. *Deviant Behavior*, 1-21.

Chamberlain, A. W., & Wallace, D. (2016). Mass reentry, neighborhood context and recidivism: Examining how the distribution of parolees within and across neighborhoods impacts recidivism. *Justice Quarterly, 33*(5), 912-941.

Clear, T. R. (2009). *Imprisoning communities: How mass incarceration makes disadvantaged neighborhoods worse*: Oxford University Press.

Clear, T. R., Rose, D. R., & Ryder, J. A. (2001). Incarceration and the Community: The Problem of Removing and Returning Offenders. *Crime & Delinquency, 47*(3), 335-351.

Clear, T. R., Rose, D. R., Waring, E., & Scully, K. (2003). Coercive mobility and crime: A preliminary examination of concentrated incarceration and social disorganization. *Justice Quarterly, 20*(1), 33-64.

Clear, T. R., Waring, E., & Scully, K. (2005). Communities and reentry: Concentrated reentry cycling. *Prisoner reentry and crime in America*, 179-208.

Cohen, M. L., & Zhang, X. D. (1988). The difficulty of improving statistical synthetic estimation. *Statistical Research Division Report Series*. U.S. Bureau of the Census.

Dhondt, G. (2012). The bluntness of incarceration: Crime and punishment in Tallahassee neighborhoods, 1995 to 2002. *Crime, law and social change, 57*, 521-538.

Drakulich, K. M., Crutchfield, R. D., Matsueda, R. L., & Rose, K. (2012). Instability, informal control, and criminogenic situations: community effects of returning prisoners. *Crime, Law and Social Change, 57*(5), 493-519.

Durose, M. R., Cooper, A. D., & Snyder, H. N. (2014). *Recidivism of prisoners released in 30 states in 2005: Patterns from 2005 to 2010*: US Department of Justice, Office of Justice Programs, Bureau of Justice.

Fagan, J., West, V., & Hollan, J. (2002). Reciprocal Effects of Crime and Incarceration in New York City Neighborhoods. *Fordham Urban Law Review*(5), 1551-1602.

Golledge, R. G. & Stimson, R. J. (1997). *Spatial behavior: A geographic perspective.* New York, NY: The Guilford Press.

Garland, D. (2001). The culture of control: Crime and social order in contemporary society. In: Oxford: Oxford University Press.

Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American Journal of Sociology, 91*, 481-510.

Harding, D. J., Morenoff, J. D., & Herbert, C. W. (2013). Home Is Hard to Find: Neighborhoods, Institutions, and the Residential Trajectories of Returning Prisoners. *The ANNALS of the American Academy of Political and Social Science, 647*(1), 214-236.

Hipp, J. R., & Boessen, A. (2013). Egohoods as waves washing across the city: A new measure of "neighborhoods". *Criminology, 51*(2), 287–327.

Hipp, J. R., Petersilia, J., & Turner, S. (2010). Parolee recidivism in California: The effect of neighborhood context and social service agency characteristics. *Criminology, 48*(4), 947-979.

Hipp, J. R., Tita, G. E., & Greenbaum, R. T. (2009). Drive-bys and trade-ups: Examining the directionality of the crime and residential instability relationship. *Social Forces, 87*(4), 1778-1812.

Hipp, J. R., & Wickes, R. (2017). Violence in Urban Neighborhoods: A Longitudinal Study of Collective Efficacy and Violent Crime. *Journal of Quantitative Criminology, 33*(4), 783-808.

Hipp, J. R., & Yates, D. K. (2009). Do returning parolees affect neighborhood crime? A case study of Sacramento. *Criminology, 47*(3), 619-656.

Jones, M., & Pebley, A. R. (2014). Redefining neighborhoods using common destinations: Social characteristics of activity spaces and home census tracts compared. *Demography*, *51*(3), 727-752.

Kaeble, D. (2018). Probation and parole in the United States, 2016 (NCJ 251148). *Washington, DC: Bureau of Justice Statistics*.

Kaeble, D., & Cowhig, M. (2016). Correctional populations in the United States, 2016 (NCJ-251211) *Washington, DC: Bureau of Justice Statistics*.

Kearns, A., Livingston, M., Galster, G., & Bannister, J. (2018). The Effects of Neighbourhood Offender Concentrations on the Number, Type and Location of Crimes Committed by Resident Offenders. *The British journal of criminology, 59*(3), 653-673.

Kirk, D. S. (2015). A natural experiment of the consequences of concentrating former prisoners in the same neighborhoods. *Proceedings of the National Academy of Sciences, 112*(22), 6943-6948.

Kovandzic, T. V., Marvell, T. B., Vieraitis, L. M., & Moody, C. E. (2004). When Prisoners Get Out: The Impact of Prison Releases on Homicide Rates, 1975-1999. *Criminal Justice Policy Review, 15*(2), 212-228.

Krivo, L. J., & Peterson, R. D. (2000). The Structural Context of Homicide: Accounting for Racial Differences in Process. *American Sociological Review, 65*(4), 547-559.

Kubrin, C. E., & Stewart, E. A. (2006). Predicting who reoffends: The neglected role of neighborhood context in recidivism studies. *Criminology, 44*(1), 165-197.

La Vigne, N., Visher, C., & Yahner, J. (2005). Chicago communities and prisoner reentry. *Washington, DC: Urban Institute*.

La Vigne, N. G., & Parthasarathy, B. (2005). *Returning Home Illinois Policy Brief: Prisoner Reentry and Residential Mobility*. Washington, D.C.: Urban Institute: Justice Policy Center.

La Vigne, N. G., Visher, C., & Yahner, J. (2004). Chicago prisoners' experiences returning home. *Washington, DC: Urban Institute*.

Livingston, M., Galster, G., Kearns, A., & Bannister, J. (2014). Criminal Neighbourhoods: Does the Density of Prior Offenders in an Area Encourage others to Commit Crime? *Environment and Planning A: Economy and Space, 46*(10), 2469-2488.

Logan, J. R., & Spitze, G. D. (1994). Family neighbors. *American Journal of Sociology, 100*(2), 453-476.

Lynch, J. P., & Sabol, W. J. (2001). Prisoner reentry in perspective. *Washington, DC: Urban Institute*.

Lynch, J. P., & Sabol, W. J. (2004). Effects of incarceration on informal social control in communities. In M. Pattillo, D. Weiman, & B. Western (Eds.), *Imprisoning America: the social effects of mass incarceration* (pp. 135–164). New York: Russell Sage.

Morenoff, J. D., & Harding, D. J. (2014). Incarceration, Prisoner Reentry, and Communities. *Annual Review of Sociology, 40*(1), 411-429.

O'brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & quantity*, *41*, 673-690.

Openshaw, S. & Taylor, P.J. (1981). The Modifiable Areal Unit Problem. Pp. 60-69 in *Quantitative Geography: A British View*, edited by N. Wrigley and R. J. Bennett. London: Routledge and Kegan Paul.

Petersilia, J. (2003). *When prisoners come home: Parole and prisoner reentry*: Oxford University Press.

Raphael, S., & Stoll, M. A. (2004). The Effect of Prison Releases on Regional Crime Rates. *Brookings-Wharton Papers on Urban Affairs 2004*, 207-255.

Rose, D. R., & Clear, T. R. (1998). Incarceration, social capital, and crime: Implications for social disorganization theory. *Criminology*, *36*(3), 441-480.

Sampson, R. J. (1988). Local Friendship Ties and Community Attachment in Mass Society: A Multilevel Systemic Model. *American Sociological Review, 53*(5), 766-779.

Sampson, R. J. (1991). Linking the micro-and macrolevel dimensions of community social organization. *Social Forces, 70*(1), 43-64.

Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology, 94*(4), 774-802.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy. *Science, 277*(5328), 918-924.

Seiter, R. P., & Kadela, K. R. (2003). Prisoner reentry: What works, what does not, and what is promising. *Crime & Delinquency, 49*(3), 360-388.

Simes, J. T. (2019). Place after prison: Neighborhood attainment and attachment during reentry. *Journal of Urban Affairs*, 41(4), 443-463.

Singh, B., Shaffer, M. A., & Selvarajan, T. (2018). Antecedents of organizational and community embeddedness: The roles of support, psychological safety, and need to belong. *Journal of Organizational Behavior, 39*(3), 339-354.

Slocum, L. A., Rengifo, A. F., Choi, T., & Herrmann, C. R. (2013). The Elusive Relationship between Community Organizations and Crime: An Assessment Across Disadvantaged Areas of the South Bronx. *Criminology, 51*(1), 167-216.

Stahler, G. J., Mennis, J., Belenko, S., Welsh, W. N., Hiller, M. L., & Zajac, G. (2013). Predicting Recidivism for Released State Prison Offenders: Examining the Influence of Individual and Neighborhood Characteristics and Spatial Contagion on the Likelihood of Reincarceration. *Criminal Justice and Behavior, 40*(6), 690–711.

Steinberg, J. (1979). *Synthetic estimates for small areas: statistical workshop papers and discussion* (Vol. 24). National Institute on Drug Abuse.

Visher, C. A., Debus-Sherrill, S. A., & Yahner, J. (2011). Employment After Prison: A Longitudinal Study of Former Prisoners. *Justice Quarterly, 28*(5), 698-718.

Visher, C. A., & Travis, J. (2003). Transitions from prison to community: Understanding individual pathways. *Annual Review of Sociology, 29*(1), 89-113.

von Hippel, P. T., Hunter, D. J., & Drown, M. (2017). Better estimates from binned income data: interpolated CDFs and mean-matching. *Sociological Science, 4*, 641-655.

Warner, B. D., & Rountree, P. W. (1997). Local social ties in a community and crime model: Questioning the systemic nature of informal social control. *Social Problems, 44*(4), 520-536.

Western, B. (2018). *Homeward: Life in the year after prison*: Russell Sage Foundation.

Wikström, P. (2006). Individuals, Settings, and Acts of Crime: Situational Mechanisms and the Explanation of Crime. In *The Explanation of Crime: Context, Mechanisms, and Development*, edited by Per-Olof H. Wikström and Robert J. Sampson. Cambridge: Cambridge University Press.

Wo, J. C., Hipp, J. R., & Boessen, A. (2016). Voluntary Organizations and Neighborhood Crime: A Dynamic Perspective. *Criminology, 54*(2), 212-241.

TABLES

Table 1. Summary statistics of variables used in analyses

	Violent crime rate (logged)		Property crime rate (logged)		Parolee concentration (Number of parolees logged)		Parolee embeddedness (cumulative days of parolees/1000)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2003	3.57	1.83	6.04	1.15	0.81	0.75	0.25	0.28
2004	3.55	1.83	6.05	1.11	1.04	0.83	0.37	0.33
2005	3.52	1.83	6.02	1.09	1.17	0.87	0.46	0.38
2006	3.44	1.82	5.95	1.05	1.12	0.86	0.43	0.42
2007	3.48	1.82	6.02	1.04	1.06	0.85	0.41	0.44
2008	3.38	1.81	5.91	1.02	1.07	0.85	0.37	0.44
2009	3.39	1.80	6.03	1.00	1.09	0.87	0.36	0.42
2010	3.35	1.76	5.97	1.01	1.09	0.87	0.35	0.42
2011	3.23	1.77	5.91	1.01	1.08	0.86	0.34	0.43
Average	3.43	1.81	5.99	1.05	1.06	0.84	0.37	0.40
Control variables								
Concentrated disadvantage					0.39	10.67		
Residential stability					0.02	0.69		
Income inequality					0.86	0.12		
Racial/ethnic heterogeneity					0.41	0.19		
Percent immigrants					0.20	0.13		
Percent aged 16 to 29					0.24	0.10		
Percent Black					0.19	0.27		
Percent Latino					0.39	0.30		
Population density					0.10	0.08		
Annual measures--average over years								
Total employees (logged)					5.47	1.66		
Retail employees (logged)					2.78	1.77		
Recreation employees (logged)					0.69	1.18		
Food employees (logged)					2.13	2.07		
Total voluntary organizations (logged)					0.19	0.40		

Note: N = 83,836 egohoods

Table 2. Reciprocal relationship between parolee concentration/embeddedness in egohoods and crime rates (logged) with fixed effects, cross-lagged regression models for five largest cities in Texas, 2003-2011

	Model 1: violent crime model			Model 2: property crime model		
	Violent crime	Parolee concentration	Parolee embeddedness	Property crime	Parolee concentration	Parolee embeddedness
Violent/Property crime (logged)	0.865*** (0.002)	0.015*** (0.000)	0.003*** (0.000)	0.932*** (0.002)	0.002** (0.001)	0.001 (0.000)
Parolee concentration	0.058*** (0.002)	0.801*** (0.002)		0.021*** (0.005)	0.805*** (0.002)	
Parolee embeddedness	-0.032*** (0.004)		0.771*** (0.002)	-0.044*** (0.013)		0.771*** (0.002)
Violent/Property crime (logged)^2		-0.002*** (0.000)	-0.002*** (0.000)		-0.004*** (0.000)	-0.002*** (0.000)
Parolee Concentration^2	-0.013*** (0.001)			-0.009*** (0.002)		
Parolee Embeddedness^2	0.022*** (0.004)			0.036*** (0.011)		
Concentrated disadvantage	0.004*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.003*** (0.000)	0.001*** (0.000)
Residential stability	-0.016*** (0.001)	0.018*** (0.001)	0.015*** (0.001)	-0.001 (0.001)	0.016*** (0.001)	0.014*** (0.001)
Income inequality	0.058*** (0.006)	0.075*** (0.004)	0.044*** (0.003)	0.057*** (0.004)	0.085*** (0.004)	0.044*** (0.003)
Racial/ethnic heterogeneity	0.060*** (0.004)	0.030*** (0.003)	0.050*** (0.002)	0.009*** (0.003)	0.041*** (0.003)	0.055*** (0.002)
Percent immigrants	0.047*** (0.009)	-0.147*** (0.006)	-0.033*** (0.004)	-0.013* (0.006)	-0.144*** (0.006)	-0.034*** (0.004)
Percent aged 16 to 29	-0.042*** (0.010)	-0.156*** (0.007)	-0.058*** (0.004)	-0.051*** (0.007)	-0.154*** (0.007)	-0.049*** (0.004)
Percent Black	0.273*** (0.007)	0.342*** (0.004)	0.078*** (0.003)	0.037*** (0.004)	0.372*** (0.004)	0.085*** (0.003)
Percent Latino	0.167*** (0.007)	0.221*** (0.004)	0.083*** (0.003)	0.009* (0.004)	0.245*** (0.004)	0.091*** (0.003)
Population density	-0.179*** (0.010)	0.619*** (0.016)	0.121*** (0.005)	-0.195*** (0.009)	0.593*** (0.016)	0.124*** (0.006)
Total employees (logged)	0.014*** (0.001)	0.000 (0.000)	0.002*** (0.000)	0.000 (0.001)	0.002*** (0.000)	0.002*** (0.000)
Retail employees (logged)	0.012*** (0.001)	-0.003*** (0.000)	-0.000 (0.000)	0.006*** (0.000)	-0.002*** (0.000)	0.000 (0.000)
Recreation employees (logged)	0.007*** (0.001)	0.001 (0.000)	0.001*** (0.000)	0.004*** (0.000)	0.002*** (0.000)	0.001*** (0.000)
Food employees (logged)	0.019*** (0.001)	-0.002*** (0.000)	0.001*** (0.000)	0.008*** (0.000)	0.001** (0.000)	0.001*** (0.000)
Total voluntary organization (logged)	0.015*** (0.001)	0.022*** (0.001)	0.003*** (0.001)	0.013*** (0.001)	0.024*** (0.001)	0.003*** (0.001)
Intercept	0.004 (0.004)	0.005*** (0.001)	0.006*** (0.001)	0.006*** (0.002)	0.005*** (0.001)	0.003*** (0.001)
N	83,836					

Note: Standard errors in parentheses, + p<.10, * p<.05, ** p<.01, *** p<.001

FIGURES

Figure 1. Path model depicting the reciprocal relationship between parolees and neighborhood crime controlling for neighborhood measures.

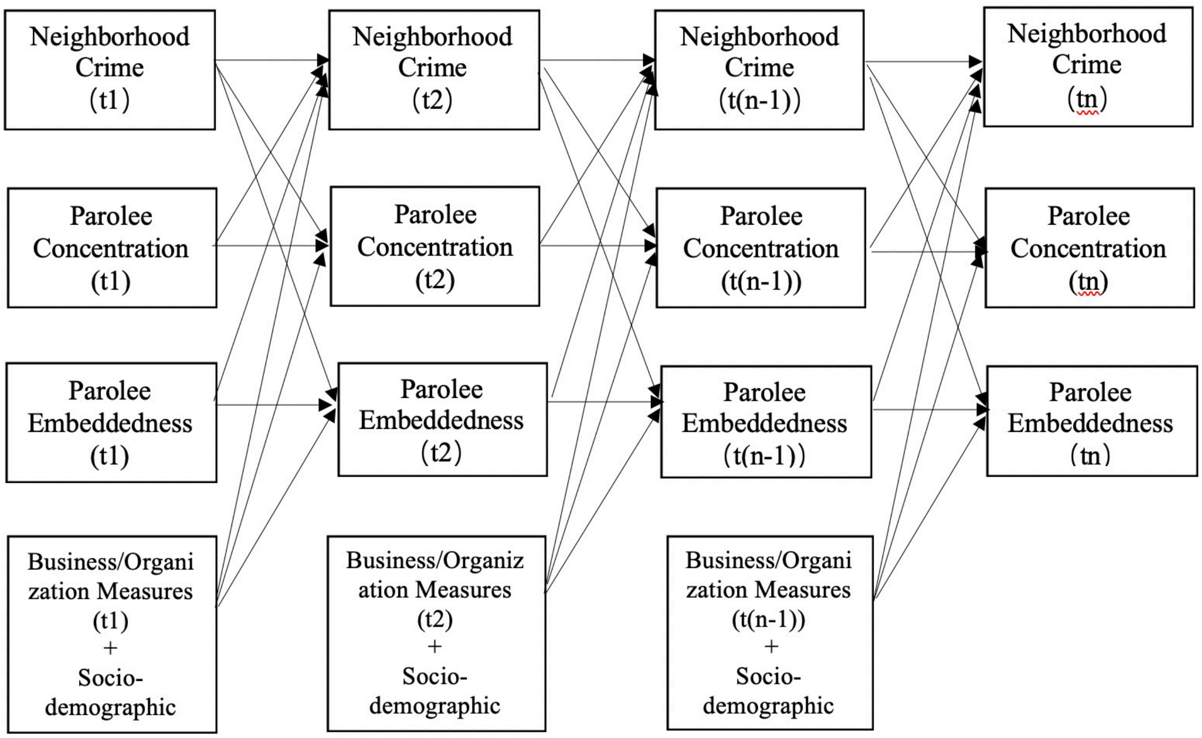


Figure 2. Effect of parolee concentration on violent and property crime in next year

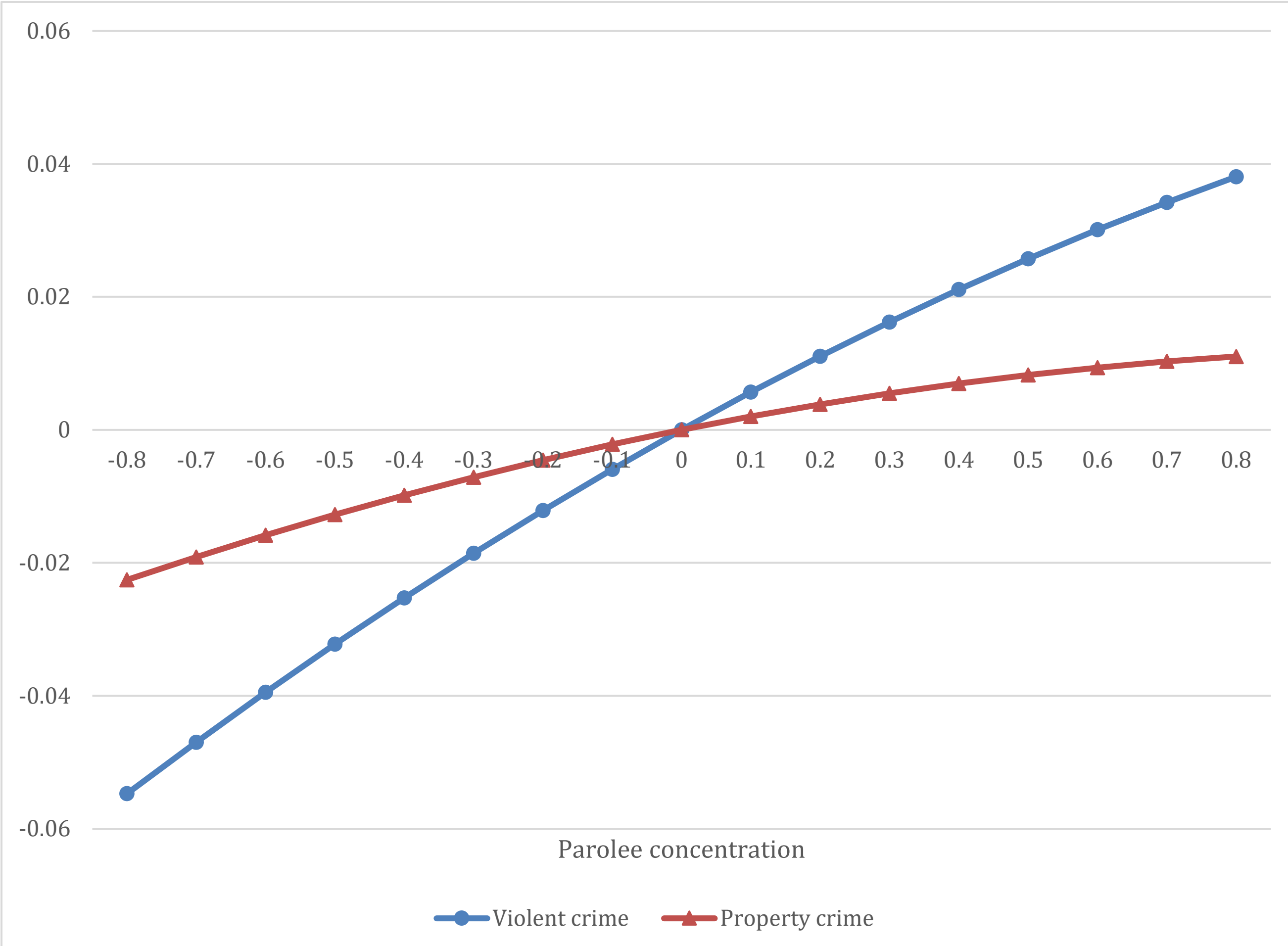


Figure 3. Effect of parolee embeddedness on violent crime and property crime in next year

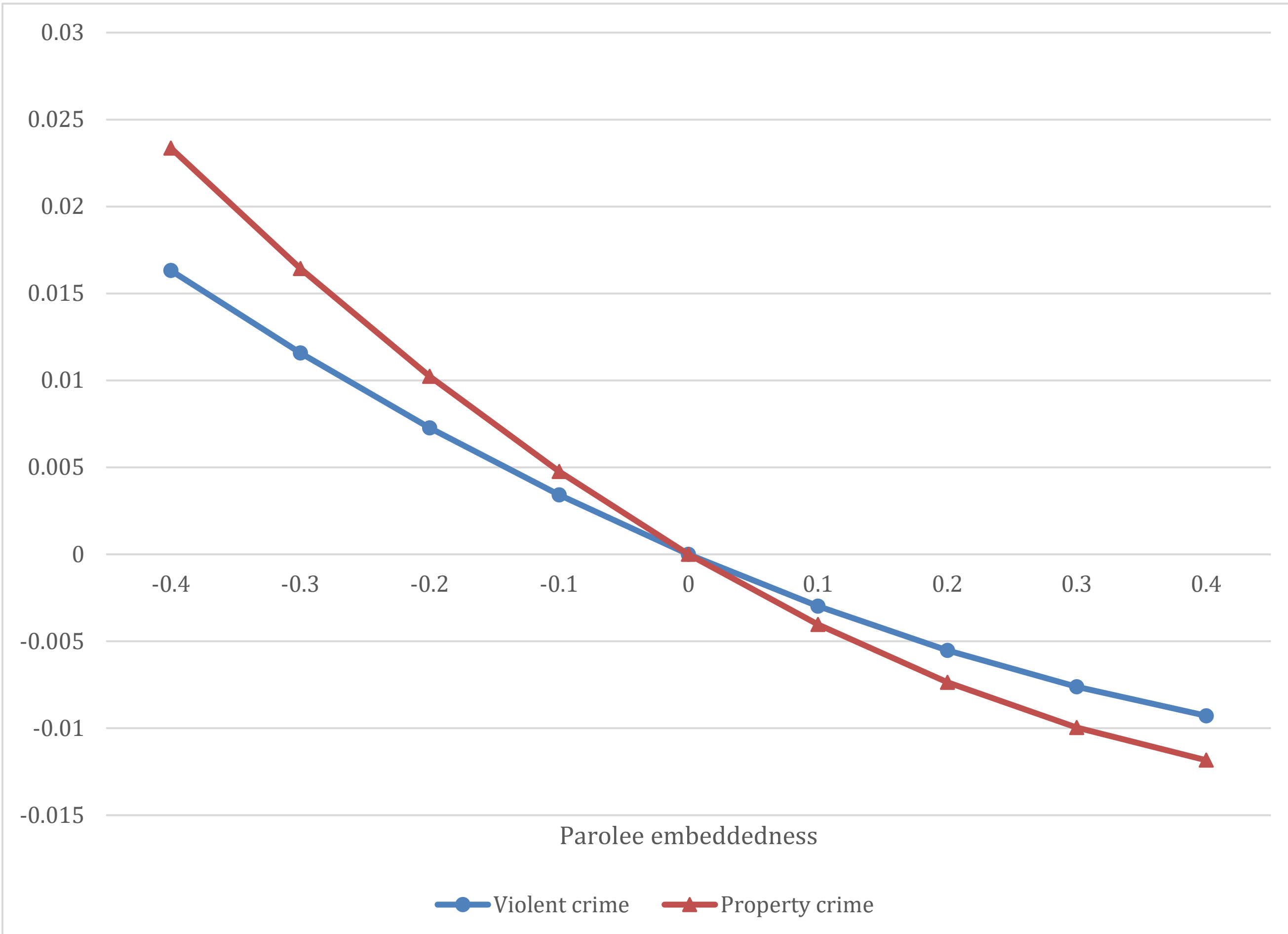
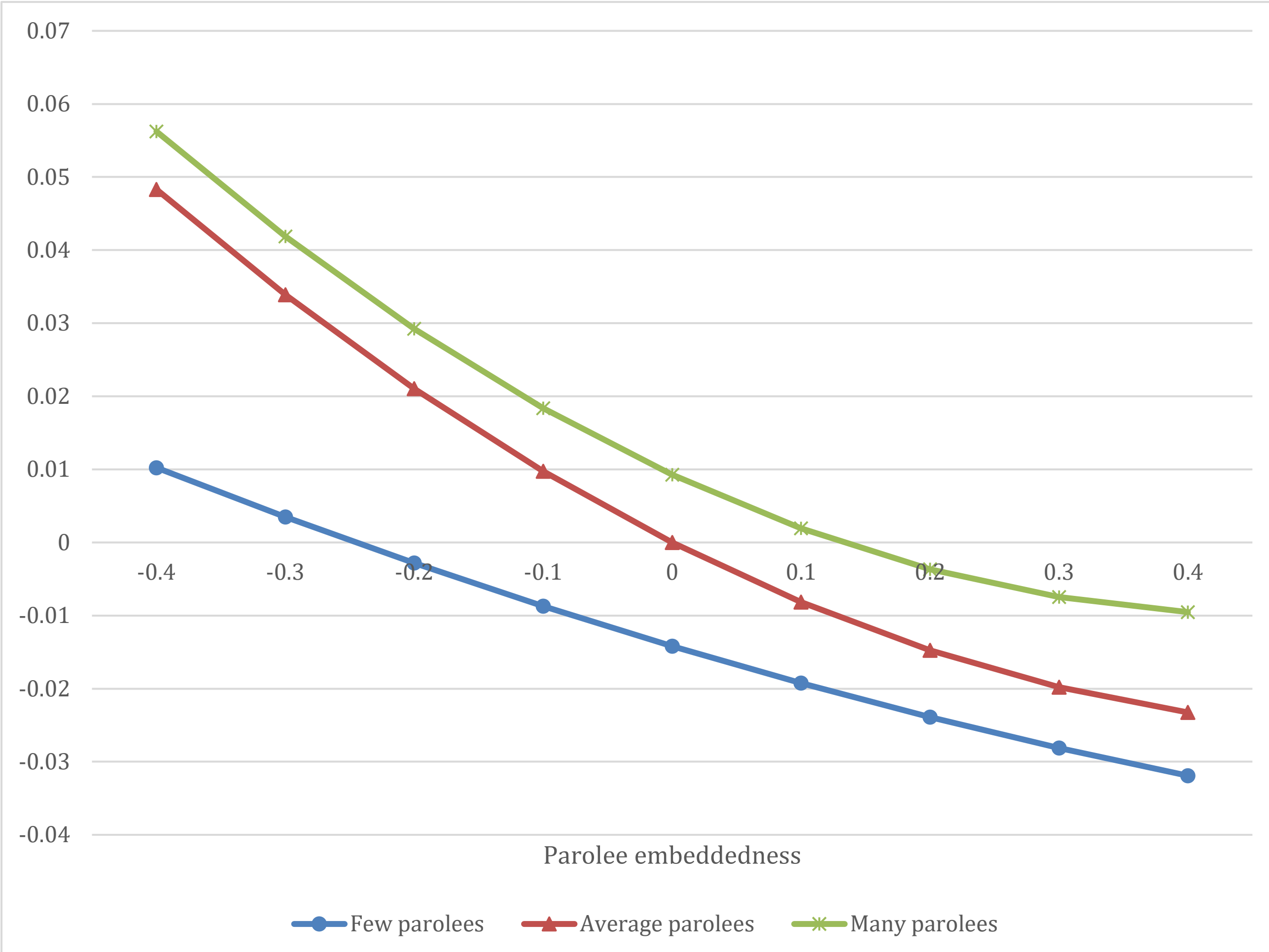


Figure 4. Effect of parolee concentration and parolee embeddedness on property crime in next year



Appendix

Table A1. Summary statistics of people on parole (averaged from 2003-2011)

	Austin	Dallas	Fort Worth	Houston	San Antonio
Number	14,920	63,737	36,142	124,611	44,983
Male	87.7%	88.3%	86.2%	89.0%	90.1%
White	31.7%	16.3%	30.6%	15.0%	14.6%
Black	38.2%	66.9%	50.7%	64.2%	14.6%
Latino	29.7%	16.4%	18.3%	20.4%	70.5%
Married	15.5%	17.5%	18.3%	15.7%	18.9%
Age 0-24	1.6%	1.1%	1.5%	1.9%	1.4%
Age 25-34	21.6%	18.9%	19.0%	22.5%	21.1%
Age 35-49	41.6%	43.0%	42.6%	41.1%	42.5%
Age 50-64	30.7%	31.6%	31.5%	30.0%	30.4%
Age 65 and up	4.6%	5.4%	5.4%	4.4%	4.6%