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Reciprocal Relationship between Returning Parolees and Neighborhood Crime Rates in Texas: A Longitudinal Study of Prisoner Reentry

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Reciprocal Relationship between Returning Parolees and Neighborhood Crime Rates in Texas: A Longitudinal Study of Prisoner Reentry

THESIS

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for the degree of

MASTER OF ARTS

in Criminology, Law and Society

by

Xiaoshuang Iris Luo

Dissertation Committee:
Professor John R. Hipp, Chair
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ABSTRACT OF THE THESIS

Reciprocal Relationship between Returning Parolees and Neighborhood Crime Rates in Texas: A Longitudinal Study of Prisoner Reentry

by

Xiaoshuang Iris Luo

Master of Arts in Criminology, Law and Society

University of California, Irvine, 2020

Professor John R. Hipp, Chair

A large body of literature documents that there is a marked increase in incarceration and people on parole in the United States until fairly recently. Empirical research has yet to sufficiently explore how people on parole returning to communities may affect neighborhood crime rates or neighborhood crime in turn influences parolees' integration into communities. Drawing on recent scholarship on mass incarceration, prisoner reentry, and macrolevel predictors of crime, this study examines the reciprocal relationship between returning parolees and neighborhood crime rates using a large sample of parolees returning to neighborhoods in the five largest cities in Texas (Austin, Dallas, Fort Worth, Houston, and San Antonio) over a nine-year time period (2003 - 2011). I employ cross-lagged regression models using structural equation modeling method to explore whether returning parolees in the former year affect the neighborhood crime rates the following year and vice versa. To fully capture these reciprocal effects, I propose a more accurate approach for measuring parolees by capturing their exposure in the community – days parolees are present in the neighborhood – and compare it to the most common approach of counting the number of parolees. Results indicate distinctions based on different measures: numbers of parolees do not have significant effect on either violent or property crime, but days of parolees in the neighborhood are significantly associated with reductions in neighborhood crime. The results suggest a strong selection effect of parolees. I highlight the dynamics of parolee reentry and neighborhoods in the era of mass incarceration.

CHAPTER 1: INTRODUCTION

Parole and prisoner reentry – the process of leaving prison and returning to free society (Visher and Travis 2003) – is a long-standing inquiry among criminologists and sociologist (Clear, Waring and Scully 2005, Clear, Rose and Ryder 2001, La Vigne and Parthasarathy 2005, Petersilia 2003), particularly in the modern era of mass incarceration (Garland 2001). The adult imprisonment rate in state and federal correctional facilities was slightly less than 200 per 100,000 U.S. residents in the late 1970s, while it goes up to about 582 per 100,000 in 2016 (Carson 2018, Zeng 2018). A consequence of this mass incarceration is the unprecedented numbers of ex-offenders returning to society. An estimated 4.5 million adults, or approximately 1 in 55 adults, are under community supervision at the year-end 2016, in which 874,800 or 13.2% of the total U.S. correctional population are on parole (Kaeble and Cowhig 2016). With the past four decades witnessing a dramatic increase in people returning to their neighborhoods on parole, there is a need for research to understand the neighborhood patterns of parole.

There is a large and growing literature on how these parolees affect neighborhood crime outcomes. Research has found that parolees have high rates of residential mobility after prison (Harding, Morenoff and Herbert 2013, La Vigne and Parthasarathy 2005), are likely to return to a relatively small number of neighborhoods (Kirk 2015), are spatially concentrated (Kearns et al. 2018), primarily in impoverished urban areas (Cadora, Swartz and Gordon 2003, Kirk 2015), have many health related issues (Baer et al. 2006) and limited employment prospects (Visher, Debus-Sherrill and Yahner 2011). One consequence of these patterns is that people coming back into communities may increase neighborhood level crime or disorder within these social spaces (Hipp, Petersilia and Turner 2010). Other research, however, documents that when people on parole go back to a community, it can be beneficial for the neighborhood through a variety of ways. Some positive effects include family reunification (Braman 2007), increasing informal social control in neighborhoods (Hipp and 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 parole return to these communities on crime patterns remains unclear.

The relationship between parolees and neighborhoods, however, is not unidirectional. A clustering of ex-offenders moving into more disadvantaged and socially disorganized neighborhoods contributes substantially to increasing neighborhood crime (Hipp and Yates 2009, Hipp, Turner and Jannetta 2010), and in turn, neighborhoods may differentially impact prisoner reentry. Although prisoner reentry is an intense personal experience, it is also a community phenomenon (Clear et al. 2005). Neighborhoods with higher social capital and greater cohesion can better accommodate a significant influx of parolees, but it is not easy for parolees to enter into these neighborhoods, rather ex-prisoners are typically concentrated in socially disorganized neighborhoods with higher crime rates (Kirk 2015). More crime in a community is tied to more arrests and incarceration, but also more prisoners returning to or paroled to the same or similar communities (Harding et al. 2013). Neighborhood crime may affect prisoner reentry by attracting more parolees residing in some neighborhoods than others (Chamberlain 2016). Empirical research has yet to sufficiently explore how people on parole returning to communities may affect neighborhoods as a whole and neighborhood crime rates in particular, and whether crime at the neighborhood level in turn may influence parolees' reintegration into communities.

To begin to untangle these effects, I test two different neighborhood level measures of returning parolees. Generally, researchers have employed the number of people on parole in a neighborhood as their key measure to examine the consequences of reintegration for crime or other outcomes. One challenge with this approach is that it does not capture the extent of neighborhoods' exposure to parolees because a raw count of these individuals does not capture the amount of time that these parolees spend in these neighborhoods after leaving prison. Since parolees show high rates of residential mobility (Harding et al. 2013) and any positive effect of being in a neighborhood requires a certain degree of neighborhood embeddedness, the amount of differing time parolees spending in neighborhoods may in turn have distinct effect on neighborhood crime outcomes. I propose a novel measure – days parolees spend in the neighborhood – to capture the actual time parolees are present in the neighborhood and assess how it affects (or is affected by) neighborhood crime.

This article explores the reciprocal relationship between people on parole and neighborhood crime using unique 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 the second largest state in the United States by area and population, Texas is also among the top states with high number of populations 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). How returning parolees affect neighborhood crime and vice versa is a crucial empirical question for researchers and policymakers, and by using longitudinal data from the largest cities in Texas, I examine a key piece of reentry during the era of mass incarceration.

CHAPTER 2: BACKGROUND

The Ecology of Social Disorganization

Researchers have uncovered several factors that influence individuals' transitions from prison back into a community. One vein of research has largely drawn on social disorganization theory (Shaw and McKay 1942), focusing on how neighborhood ecological characteristics, such as residential mobility, poverty, single parent household, affect one's illegal activities (Sampson 1988). The theory posits that neighborhoods with more concentrated disadvantage, residential instability, and racial/ethnic heterogeneity tend to have more social disorder, less social cohesion, have community social networks being disrupted and social interactions in the neighborhoods getting reduced (Bursik 1988). As a consequence, it impedes the level of collective efficacy that neighborhood residents need to respond to such problems and build informal social control (Sampson and Groves 1989, Sampson, Raudenbush and Earls 1997). All of these socially disorganized neighborhood characteristics significantly contribute to higher rates of crime.

Among which, residential stability is key for establishing social networks and social ties and reinforcing social cohesions among neighbors, and it further enables informal social control and collective action in the neighborhood. Some residents are forcibly removed from their communities to prisons or jails due to incarceration, while others return either on parole or probation or complete release, which is conceptualized as "coercive mobility" by Clear and his colleagues (2003). Parolees under community supervision are at high risk of mobility (Harding et al. 2013) since a violation of their parole would lead to their return to prison. In addition, people on parole living in disadvantaged communities experience social network disruption which can increase neighborhood disorder, thereby decreasing the resources and services available for reintegration (Fagan, West and Hollan 2002). This functions in a reciprocal way, by increasing parolees' risks of residential mobility. In poor communities there are high rates of residents cycling in and out of prison, which impedes neighborhood stability, further leading to high rate of crime. The cycling of offenders between prison and the community implies that increases in neighborhood crime occur due to the removal of individuals from the community through incarceration (Chamberlain and Wallace 2016, Clear et al. 2003).

Parolees and Neighborhood Crime

The Impact of Parolee Releasing on Neighborhood Crime

In the era of mass incarceration, a large number of ex-offenders return to society and reunify with families, but the pattern of returning to neighborhoods for parolees is not random. Rather, these parolees generally return to the neighborhoods or places with similar characteristics as their home neighborhood (Harding et al. 2013). A common phenomenon is that parolees are predominantly concentrated in impoverished urban areas (Cadora et al. 2003, La Vigne, Visher and Yahner 2005) and reside in disadvantaged neighborhoods with little support for prisoner reentry (La Vigne et al. 2005). Disadvantaged neighborhoods already have significantly higher rates of unemployment, poverty, single family household, social disorder and crime (Lynch and Sabol 2001). Therefore, an influx of parolees in these disadvantaged neighborhoods might further erode these communities and increasing number of parolees in a neighborhood does have a direct effect on neighborhood crime rates (Hipp and Yates 2009).

Furthermore, Clear, Rose, and Ryder (2001) argued that the return of prisoners to neighborhoods as parolees increases crime by exacerbating the residential instability of the neighborhood. Building on social disorganization theory (Sampson 1988), Kubrin and Stewart (2006) find that parolees returning to more residentially stable areas have lower rates of reoffending, controlling for several individual-level factors. However, Harding and colleagues (2013) document that it is hard for parolees to find a stable residence and parolees experience high rates of residential mobility after prison making it more difficult to return to their former neighborhoods. The frequent mobility of parolees is also associated with reducing a source of informal social control in neighborhoods, which in turn could lead to more neighborhood crime (Hipp et al. 2010).

Beyond that, the effect of returning parolees on neighborhood crime could result from parolee themselves' being prone to criminality and also the increased pool of motivated offenders through network links with other released parolees. Parolees are generally given little support or assistance when they leave prison and typically have a lower level of education and job skills (La Vigne et al. 2005). Their employment prospects are often damaged by imprisonment, and their social network connections with employment opportunities are also disrupted (Western 2006). They face discrimination in the job market by employers who are less likely to hire individuals with a prior criminal record (Pager 2003). Exacerbating these difficulties, parolees often face the huge burden of paying fines and fees after release, which may, to some extent, trigger parolees returning to criminal activity. Living in disadvantaged neighborhoods, a lack of employment opportunities, disrupted social networks, facing social stigma as an ex-offender, bearing a huge burden of fees and fines, and having few resources to help on the outside, all contribute to parolees' prone to criminality.

Parolees in general are more likely to commit crime, as we see from the high recidivism rates among ex-offender (Alper, Durose and Markman 2018, Durose, Cooper and Snyder 2014). For example, research shows that the percentage of re-arrests among parolees is statistically high, about 4 in 9 (44%) released prisoners were arrested during the first year following release and about 68% of the prisoners rearrested within 3 years, according to a large study of criminal recidivism during a 9-year follow up period from 2005 to 2014 conducted by the Bureau of Justice Statistics (Alper et al. 2018). Drawing on the recidivism literature, parolees have a high tendency to return to criminal activities and, to a certain extent, this recidivism contributes to neighborhood crime rates. In addition, researchers suggest that parolees who enter a neighborhood increase the pool of motivated offenders (Hipp and Yates 2009), and all else being equal, they will increase the level of crime. Parolees can indirectly lead to higher neighborhood crime by reactivating network links that entice others into committing crimes. Research also finds that the density of prior offenders in a neighborhood is positively associated with the number of newly active crime offenders (Livingston et al. 2014). Thus, the effects of parolees on neighborhood crime are due to the higher chance of parolees' criminal activities, but also the crimes committed by motivated offenders.

Research also indicates that conviction for certain types of crimes is a strong predictor of recidivism and prisoners with more serious commitment offense (e.g., violent offense, property offense) account for higher percentage of post-release arrest than those with less serious commitment offense (Durose et al. 2014). In addition, parolees constitute a larger proportion of serious crime arrests such as murder, robbery and burglary (Langan and Levin 2002). Parolees with a longer record of serious and violent crimes could exhibit more danger to the communities and increase neighborhood crime rates, one of reasons being that they are likely more hardened criminals who are more likely to commit crimes in the future (Hipp and Yates 2009). On the contrary, parolees with minor offense or sex offense may not pose huge impact on neighborhood violent crime or property crime. Thus, I expect how parolees with record of conviction on different seriousness of offense (i.e., different *types* of parolees) affect neighborhood crime may also vary.

The Impact of Neighborhoods on Parolee Reentry

Although parolees may affect informal and formal social control at the neighborhood level, it is also possible that the level of social control and social capital in a neighborhood is important for parolees' integration into free society, especially concerning several obstacles and pressure ex-offenders facing in various aspects from the criminal justice system, society in general, neighborhoods, and families (Clear, Rose and Ryder 2001). Among which, there are four domains: the problem of stigma, financial impacts, issues regarding identity, and the maintenance of interpersonal relationships. Given the well-documented difficulties that parolees face in attempting to reintegrate into the community (Petersilia 2003), it is plausible that neighborhood characteristics are important for parolees' successful reintegration.

The social capital of the neighborhood is crucial in allowing the neighborhood to successfully reintegrate parolees into their communities. When neighborhoods have abundant social resources, they are able to provide support or assistance to parolees, such as different programs aiming at job training, finding work, provide consulting, build social connections, etc. All of these resources may help parolees avoid returning to criminal activity. Research has suggested that parolees that are integrated into the neighborhood through family support and social networks are less likely to recidivate, while those returning back to communities with fewer sources of social support and limited employment opportunities are more likely to recidivate (La Vigne et al. 2005). It is also possible that the informal social capital in a neighborhood may help in integrating parolees into the community. Given the evidence suggesting that neighborhoods with greater residential stability will have more informal social ties (Logan and Spitze 1994, Sampson 1988, Sampson 1991, Warner and Rountree 1997), this stability may help neighborhoods respond to the possible negative presence of parolees.

Some prior research has found that a positive relationship between parolees and neighborhood crime, with more parolees present in neighborhoods associated with higher crime rates (Chamberlain 2016, Hipp and Yates 2009, Kovandzic et al. 2004, Raphael and Stoll 2004). However, it is likely that high-crime neighborhoods attract more parolees, as most offenders return to the same or similar neighborhoods before arrested and these neighborhoods are more likely to be disadvantaged places and have high crime rates (Harding et al. 2013). Due to the difficulties and challenges, financial hardship, or stigmatization that parolees face, it would be easier for parolees to enter disadvantaged neighborhoods. In part, crime can also affect the presence of parolees in a neighborhood because high-crime neighborhoods attract parolees. High-crime neighborhoods may offer more opportunities to an offender, tend to be more affordable, and may provide cover as returning parolees try to reintegrate into society. For the current study, I examine this reciprocal relationship between parolees and neighborhood crime.

Although some previous research shows that parolees have a positive effect on neighborhood crime, whether, and if so, how different social contexts moderate this parolee-crime relationship also needs conversation. Given that the primary effects of parolees on crime are through residential instability, disadvantage, lack of support services (i.e., nonprofit organizations or institutions), and the concentration of people on parole (challenges of getting jobs, lack of education, deviant peers, etc.) from above argument, parolees returning to neighborhoods with diverse contexts may not generate equal effects on neighborhood crime. Neighborhoods with higher levels of formal social control, such as lower neighborhood disadvantage and higher residential stability, have greater economic potential, better social resources, more social ties and greater collective efficacy (Sampson et al. 1997), which enhances the ability to reintegrate parolees and provide them more employment opportunities and social networks and support (La Vigne et al. 2005). Likewise, informal social control such as voluntary organizations is also crucial in this parolee-crime relationship. Neighborhoods with more voluntary organizations experience reductions in crime (Wo, Hipp and Boessen 2016), and they also have the capacity to provide social services parolees often need after prison, which could further lower the likelihood of parolees' criminal activity. Thus, it is possible to see that social context could moderate the potentially damaging effects of parolees on neighborhoods and I examine this moderating effect in my analyses.

Selection Effect of Parolees

It is widely documented in the literature that parolees are associated with neighborhood crime, however, there is less agreement on how to measure parolees in neighborhoods. A typical way to measure parolees is using the number or counts of parolees released to the neighborhood either monthly or annually, which is one possible strategy. Due to the high probability of parolees' mobility (Clear et al. 2003) and high recidivism rates (Alper et al. 2018), how long neighborhoods are exposed to parolees is unknown when simply capturing the number of parolees, especially for studies using longitudinal annual data. Because of the failure to account for the time parolees are present in the neighborhood, it is hard to see how exactly neighborhoods are affected by (or affect) returning parolees. For example, a neighborhood has two parolees in one year, but these two parolees rapidly commit crime again and go back to prison, and therefore they don't spend much time in the neighborhood. Another neighborhood also has two parolees in that year, but they spend the entire year in that neighborhood. Do the parolees affect neighborhoods in the same way? Do they contribute to neighborhood crime similarly even if they stay in the neighborhood for different length of time? Without a more accurate approach for measuring parolees, it is difficult to answer these queries.

Here, I propose another approach to capture parolees, that is, the days parolees are present in the neighborhood. There are, however, some limitations to this strategy. One problem is that by using days parolees are present in the neighborhood, the results of parolees' impact on neighborhood crimes may rely on capturing the effect of more good parolees who may stay in the neighborhoods longer, which I call the *selection effect* of parolees. Thus, it may risk over-estimating the differential effects of crime-prone parolees and those pro-social parolees and their period of time in the neighborhood on neighborhood crimes due to implicit selection. Whether this selection effect of parolees exists in my study remains uncertain and I hope to untangle it through my analyses. To my knowledge, this is the first study to map out these processes using different measures of parolees and comparing the different effects.

CHAPTER 3: DATA AND METHODOLOGY

Data

The data for my research comes from all paroled inmates released in Texas and returning to the community from 2003 to 2011.[1] Data were obtained directly from the Texas Department of Criminal Justice (TDCJ). The data provide information on when these people started on parole and when they ended. Parolees were followed until the end of their parole (revoked or discharged) or until July 2012, which is the date when the data stopped tracking them. The TDCJ also tracked where offenders on parole resided after release and I geocoded parolees' home addresses using Google and ArcGIS ArcMap 10.6. Nearly all parolees reported an address, and about 90% of unique addresses were geocoded to an exact X-Y coordinate and joined to a census tract. For crime data, I obtain crime information from the five largest cities in the state of Texas from 2003 to recent years: Austin, Dallas, Fort Worth, Houston, and San Antonio. Annual crime data cover Part I crimes, and I geocode the addresses of the crime events to X-Y coordinate and aggregate them to tract level in order to match with the census tract data.

I integrate other sources of publicly available data to contextualize the communities to which these parolees return. Specifically, I merge the 2000 U.S. census tract data with the parolee data to capture sociodemographic information. Overall, I have a total of 5,265 tracts in Texas and 1,613 tracts with crime data. In addition, I capture business information with *ReferenceUSA* data from *Infogroup.* Reference USA is an annual dataset that contains

[1] The full data obtained from TDCJ are from 2000 to 2012. But there are some uncertainty issues about the number and days of parolees in the years 2000 to 2002 and the data only capture a half year of the parolees' information in 2012, thus I estimate my models from 2003 to 2011.

geographic information so that I can locate businesses at the tract level and ultimately merge it with other data sources. As formal organizations help a neighborhood reintegrate parolees with the community, I also include data on voluntary organizations. These data come from the National Center for Charitable Statistics (NCCS) and contain information on exempt organizations from the Internal Revenue Service's Business Master File.[2] I geocode these organizations based on the provided address and place them into the appropriate census tract. All data used above are harmonized to 2010 census tract boundaries.

Outcome Measures

Neighborhood Crime Rates. I use crime rates per 10,000 population in a census tract per year as my crime measure, which are computed by dividing the number of crime events in a tract by the total population in a given year, then multiplying by 10,000. Crime events are aggregated into yearly totals for violent crime (homicide, robbery, and aggravated assault) and property crime (burglary, larceny, and motor vehicle theft), then I compute the crime rates per 10,000 population for aggregated violent crime rates and aggregated property crime rates. All crime variables are log transformed to account for the skewed distribution.

Parolees. To examine the relationship between the presence of parolees returning to neighborhoods and neighborhood crime, I construct a measure of *days of parolees* in a census tract in a given year. This was calculated by taking the number of days parolees residing in a particular tract in a given year based on the start date and end date of

[2] 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.

parolees' status. If parolees start and end the status as parolee within the same year, then this measure equals the end date subtracting the start date. If the days of parolees spread multiple years, then days are computed for each year (only counting the days parolees stay in the neighborhood for that year) since it is an annual measure. Due to the high skewness value of days of parolees, I log transform it. I also construct *number of parolees* residing in a particular tract in a given year. Here, anyone who has stayed in the neighborhood in that year, regardless of duration, is counted as one parolee. Additionally, I am interested in how different types of parolees may contribute to neighborhood crime similarly or differently. Thus, I create several other parolee measures – both numbers and days – based on the seriousness or the types of offense parolees have committed. Specifically, there are four types of parolees in my analyses – violent offense parolees, drug offense parolees, sex offense parolees, and other offense parolees, and the days measures are log transformed.[3]

Exogenous Variables

Time Invariant Variables. Several additional time-invariant control variables from 2000 census are included in the models to account for certain neighborhood characteristics. The measure of *residential stability* is constructed using principle components. Three variables are combined here to create residential stability, including average length of residence, percent of households that moved into their residence within the last five years, and percent homeowners. Another measure that largely impacts neighborhood crime is *concentrated disadvantage*, which is a measure created based on a

[3] I run all the analyses for these four different types of parolees but only present the results of the first three types of parolees since there is no interesting result about other offense parolees. Results are available upon request.

factor analysis using five variables: percent of residents below poverty, percent unemployed, percent single parent households, average home value, and average income. Racial composition of neighborhoods, that is, the percentage of different racial groups among the neighborhood, is another predictor for the analyses, in which I control for *percent black* and *percent Latinos* variables. I capture the *racial/ethnic heterogeneity* of the neighborhood with a Herfindahl index of five racial/ethnic groups. To take into account relative inequality, I include the *Gini inequality index*. I also include *percent of immigrants in the neighborhood* in my analyses. Another factor of crime is age, in which I have controlled for *percent of young people (percent of individuals of age 16 to 29)* in the tract. I also control for *population density* per square mile.

Time Varying Variables. Besides time invariant variables, I am also able to take into account several time varying variables across different waves of these longitudinal data. Research shows that business is an important predictor of neighborhood crime. I control for number of employees in the total enterprises, retail enterprises, recreation enterprises, and food enterprises as business measures, which are captured in the Reference USA data. All of these measures are allowed to vary from year to year. To account for the skewness of these measures, I log transform them. Voluntary organizations help a neighborhood reintegrate parolees with the community, following previous research (Hipp and Yates 2009), I include a measure of *total number of voluntary organizations* in the tract, which comes from the National Center for Charitable Statistics data. Different organizations provide different services, and I include several organizations that mainly provide services related to parolees, including mental health service, crime, care, abuse, legal service, vocation, food, recreation, and neighborhood. I then sum these organizations up together to get the total number. Likewise, I natural log transform the measure of number of organizations.

Analytic Strategy

Since I am capturing the reciprocal relationship between neighborhood crime and parolees, I employ structural equation modeling (SEM) methods with simultaneous equations in my analyses. Specifically, using longitudinal data on neighborhoods, I estimate a series of cross-lagged equation models, a procedure that allows me to estimate the correlations between error terms of each outcome variable in adjacent time periods. Additionally, I am also able to constrain the coefficients of independent variables to be equal over waves and test the consequences of this for model fit (Hipp, Tita and Greenbaum 2009, Hipp and Wickes 2017). I model one-year lags given that crime responding to parolee reentry likely requires a year to capture the effect. Thus, my model specifies that the presence of parolees in a year may causes neighborhood crime in the next year while taking into account the one-year lag of crime itself and controlling for a variety of additional time varying and time invariant neighborhood-level factors. I include all these neighborhood measures at the first time point year 2001 of the 2000 Census. It is also possible that high-crime neighborhoods would attract the residence of more parolees. To examine the effect of crime on parolees, I estimate the one-year lag of crime on parolees by also considering the one-year lag of parolee itself. The theoretical model is depicted in Figure 1.

[FIGURE 1 ABOUT HERE]

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

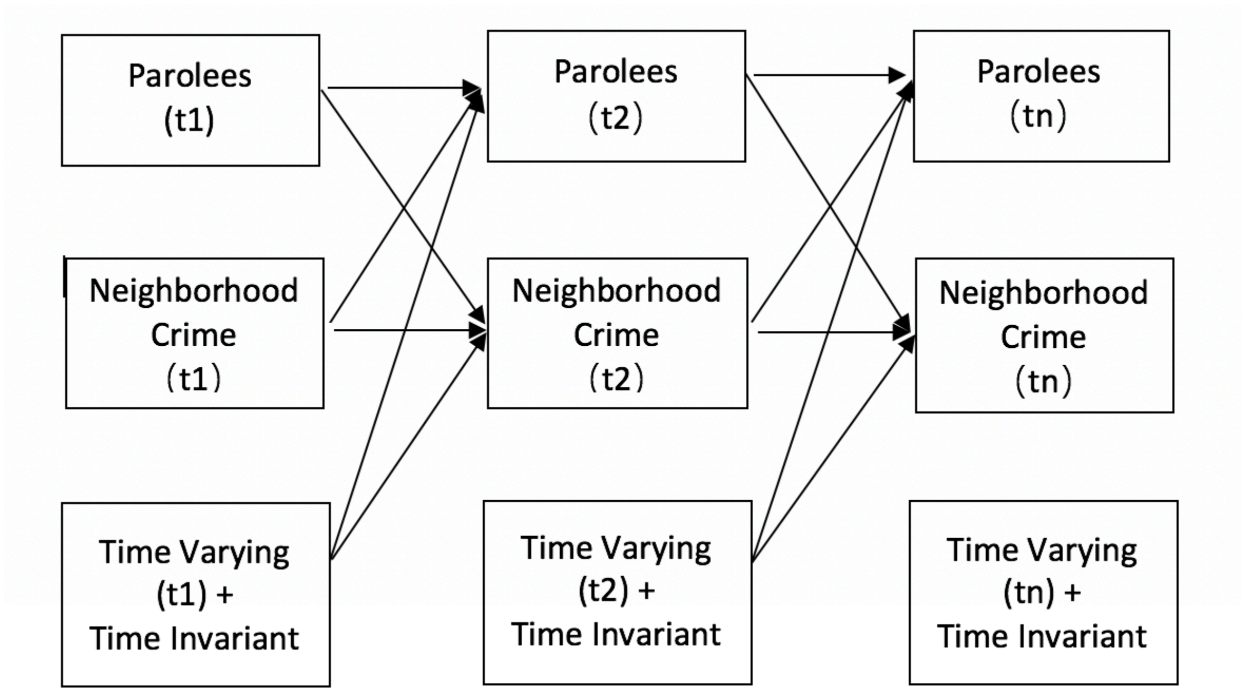
$$\text{Crime}_{it} = \boldsymbol{\alpha}_{it} + \boldsymbol{\beta}_{1t}\textbf{Parolee}_{i(t-1)} + \boldsymbol{\beta}_{2t}\text{Crime}_{i(t-1)} + \boldsymbol{\beta}_{3t}X_{i(t-1)} + \boldsymbol{\beta}_{4t}Z_i + \boldsymbol{\varepsilon}_{it} \quad (1)$$

$$\text{Parolee}_{it} = \boldsymbol{\alpha}_{it} + \boldsymbol{\beta}_{1t}\textbf{Crime}_{i(t-1)} + \boldsymbol{\beta}_{2t}\text{Parolee}_{i(t-1)} + \boldsymbol{\beta}_{3t}X_{i(t-1)} + \boldsymbol{\beta}_{4t}Z_i + \boldsymbol{\varepsilon}_{it} \quad (2)$$

where Crime_{it} is the outcome variables of logged neighborhood-level violent crime per year *t* and logged neighborhood-level property crime per year *t*. My outcome Parolee_{it} includes one of my measures of parolees (numbers of parolees or logged days of parolees) for census tract i which are measured at time *t*, $\boldsymbol{\alpha}_{it}$ is an intercept at each time point, $\boldsymbol{\beta}_{1t}$ is a vector that captures the relationship between parolees and neighborhood crime at the previous time point (*t-1*), in which I have constrained the effect for different waves to be equal. I also control for the one-year lagged outcome variable in my models, with coefficient captured in $\boldsymbol{\beta}_{2t}$ vector. $X_{i(t-1)}$ is a matrix of time varying variables and the constrained equal coefficients for different waves are captured in $\boldsymbol{\beta}_{3t}$ vector. Z_i is a matrix of several time invariant neighborhood-level control variables at the first time point of year 2001 with the accompanying coefficients captured in $\boldsymbol{\beta}_{4t}$ vector, where the coefficients for different waves are also constrained to be equal. Finally, $\boldsymbol{\varepsilon}_{it}$ is an error term with an assumed normal distribution. In addition, I have included the covariance of crime at time *t-1* and time *t*, covariance of parolees at time *t-1* and time *t*, and covariance between crime and parolees at time *t-1* and time *t* when estimating the models.

Based on above mentioned theoretical path models and simultaneous equations, I estimate a series of structural equation models in Stata 15.0 (StataCorp, College Station, TX) by running these models simultaneously. SEM is a method to account for instances of simultaneity between predictors and outcomes (Wooldridge 2010). I have controlled for both time-varying and time-fixed predictors in my analyses and the SEM application can accommodate and provide me the ability to control for simultaneity between the numbers or days of parolees and the crime rate in a given year. In addition, I use full information maximum likelihood (FIML) to handle missing data in SEM (Allison 2012).

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



Note: The outcome variables include violent crime rate, property crime rate and parolees (counts and days). Time varying measures include residential stability, concentrated disadvantage, percent black, percent Latinos, racial/ethnic heterogeneity, Gini inequality index, percent of immigrants, percent of young people, and population density. Time invariant measures include number of employees in total enterprises, retail enterprises, recreation enterprises, and food enterprises, and total number of voluntary organizations.

CHAPTER 4: RESULTS

Table 1 presents the summary statistics of the variables used in the analyses. To get a sense of the magnitude of my measures, I list the mean and standard deviation of violent crime, property crime, different measures of parolees, and time invariant and time varying measures averaged for my time period, and it is an aggregated statistic for each census tract in the five largest cities of Texas (Please see the full summary statistics of key measures for each year in Appendix Table A1). Overall, during this 9-year time period, the average logged violent crime rate per 10,000 population is 3.25 with a standard deviation of 1.59 per census tract. For logged property crime rate per 10,000 population, the mean value is 5.52, and standard deviation is 1.66. The mean value of logged days of parolees averaged is 5.74 with a standard deviation of 2.44, and the mean number of parolees averaged across 9 years is 6.59 with a standard deviation of 8.02. When breaking this down to different types of parolees, the mean number of drug offense parolees per census tract is the highest, 2.08, but higher variation comparing to violent offense and sex offense parolees. Regarding the days of parolees, the mean value of logged days of drug offense parolees averaged is still the highest, 3.78, and sex offense parolees the lowest, 0.56. Drug offense parolees stay relatively longer in the communities than other offense parolees, comparatively, sex offense parolees do not live that long in the neighborhoods.

[TABLE 1 ABOUT HERE]

Relationship between Returning Parolees and Crime

To examine the simultaneous relationship between parolees and crime, Table 2A and 2B present a series of SEM models with outcome variables of parolees – either counts or days – and violent crime and property crime, controlling for a variety of time varying and time invariant measures. First, I present the goodness of fit for all models using SEM and they all show a good model fit. For example, in model 1 Table 2A, the root mean squared error of approximation (RMSEA) is 0.032, and the comparative fit index (CFI) is 0.970, indicating a good model fit. Specific to my models, Model 1 and 2 test the reciprocal relationship between parolees and violent crime rates and property crime rates, respectively, and crime as the outcome variable is shown in one column and parolees as the outcome in another column. For example, in the column of violent crime in Model 1 Table 2A, it shows whether the presence of the number of parolees in a year in the tract leads to higher levels of violent crime rates in the following year by taking into account the one-year lag of violent crime rates. To make the interpretation of these results easier to follow, I present the result of parolees' effect on crime – either violent crime or property crime – first, then move to any effect neighborhood crime has on parolees. As I would expect, the one-year lag of violent crime rates has a strong positive effect on violent crime rates in the following year. The coefficient of violent crime is 0.965, indicating a 100% increase in violent crime rates in year t-1 is expected to increase violent crime rates in the following year by almost 97%, holding other variables constant. However, in Table 2A, I found no evidence that the number of parolees living in a neighborhood has any significant effect on either violent crime rates or property crime rates, controlling for a variety of covariates. In previous research, evidence shows that more parolees lead to more violent crime and property crime in the neighborhood (Chamberlain 2016, Hipp and Yates 2009), and my results call these findings into question.

Table 2B replicates this model above but uses days of parolees living in neighborhood as the measure of parolee embeddedness. Surprisingly, by using days of parolees compared to counts of parolees, these results tell a very different story. which relates to my previous statement about the *selection effect* of parolees in this parolee-crime relationship. In Model 1 Table 2B, the days of parolees residing in the tract in one year have a significant negative effect on violent crime rates the following year. With a one percent increase in days of parolees, the violent crime rate is expected to decrease by 0.3 percent. Similarly, I see a significant negative effect of days of parolees on property crime. A one percent increase in the days of parolees living in a neighborhood in the prior year is expected to decrease the property crime rates in the next year by 0.5 percent, holding other variables constant (Here, both the crime variable and parolee variable are log transformed, so I use percent change in the explanation).

[TABLE 2 ABOUT HERE]

The results of effect of other neighborhood measures on crime are consistent with previous research. For example, in Table 2A, residential stability is negatively associated with violent crime rates and property crime rates: with a one unit increase in residential stability, the violent and property crime rates in the tract is expected to decrease by 1.3 and 0.8 percent, respectively. Concentrated disadvantage has a significantly positive effect on violent crime rates. Both percent Black and percent Latinos are positively related to violent and property crime rates. There is also evidence that higher population density contributes to higher violent crime rates. Among business measures, the number of employees in total enterprises in one year has a significant positive effect on violent crime rate the following year. Other than that, there is no significant effect of other business measures on either violent crime or property crime. The number of voluntary organizations in the tract also leads to higher level of violent crime rates, and property crime rates, though the latter is marginally significant.

Regarding the effect of crime on parolees, there is no evidence showing that the violent crime rate affects the numbers of parolees returning to communities and no evidence showing that higher property crime rates would attract more parolees returning to the neighborhood (Table 2A). Most of the neighborhood measures have significant effects on parolees returning to community, no matter if it is number of parolees or days of parolees. For instance, concentrated disadvantage, as I would expect, is positively associated with parolees: one unit increase in concentrated disadvantage results in a 211.3 percent increase in the days of parolees in the tract, holding other variables constant (Table 2B). Number of employees in recreation and food enterprises in one year is positively associated with returning parolees the following year. What is more, there is strong evidence that voluntary organizations in the tract are associated with more parolees residing in the neighborhood. One percent increase in the number of voluntary organizations in year one in the tract results in 2.6 percent increase in the days of parolees in the next year when controlling for crime rates and other variables. On the other end, when examining the effect of crime on days of parolees, the coefficient of one year lag of violent crime rate is negative and not significant, but property crime is found to contribute to less days parolees reside in the community, with one percent increase in the property crime rates one year associated with 1.4 percent decrease of days of yearly parolees the following year. As I have shown before, the significant results do not hold for number of parolees as outcome variables.

I further decompose these effects by testing whether there are distinctions by the conviction offense in how neighborhoods with people on parole affect neighborhood crime. Table 3A and 3B present the reciprocal relationship between violent offense parolees, drug offense parolees, sex offense parolees and violent crime (panel A) and property crime (panel B). For models examining the relationship between numbers of parolees and crime in both panel A and panel B, I almost do not see any significant results, either one way or the other. The number of returning violent offense parolees, drug offense parolees, or sex offense parolees in one year is not associated with either the increase or the decrease of violent crime rates and property crime rates the next year in a neighborhood. And this non-significant effect also holds for the effect of crime on numbers of any types of returning parolees, that is, there is no reciprocal relationship between violent crime rates and my different types of parolees (numbers). There is one exception: the significant negative effect of crime on numbers of violent parolees, but it might be just a random result.

However, turning to the days measure of types of parolees, the selection effect of parolees is present once again. I see a negative relationship between drug offense parolees (using the days measure) and violent crime rates in Table 3B. In the fourth column of Table 3B Panel A, the coefficient of drug offense parolees (days) is -0.004 and it is significant, indicating one percent increase in days of drug offense parolees in one year results in 0.4 percent decrease in violent crime rates in the tract the following year. This suggests that parolees do not contribute to violent crime rates in the neighborhood, rather, drug offense parolees staying in the community longer are helpful for lowering violent crime rates. But days of violent offense and sex offense parolees do not have a significant effect on violent crime. In terms of the relationship between different types of parolees and property crime, both days of violent offense and drug offense parolees have a significant negative effect on property crime. The longer these parolees stay in the community in one year, the lower the property crime rate is in the following year.

[TABLE 3 ABOUT HERE]

Turning to the effect of crime rates on types of parolees (days), interestingly, one percent increase in violent crime rates in one year decreases the days of violent parolees spend in the neighborhood by 2.7 percent in a tract in the following year, holding other variables constant (Table 3B Panel A). It suggests if a neighborhood has a higher violent crime rates, violent parolees tend to stay in the neighborhood for a shorter duration. Further, property crime rates also decrease the days of violent offending parolees residing in the neighborhood. One percent increase in the property crime rates in year one is related to 2.8 percent decrease in the days of violent offense parolees in the tract the next year, holding other variables constant. There is no evidence showing that sex offense parolees contribute to the increase of property crime rates in the tract, however, if there are more property crime rates in the tract, sex offense parolees tend to live more days in the neighborhood.[4]

Moderating Effect

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[4] I also estimate a series of SEM with the reciprocal relationship between other offense parolees and crime rates, but find no evidence showing a significant relationship among other offense parolees and violent and property crime rates.

Parolees have been found to more likely reside in disadvantaged neighborhoods and have low residential stability. I therefore test whether an interaction effect exists between parolees and certain neighborhood characteristics. I focus on testing the moderating effect of concentrated disadvantage, residential stability, and voluntary organizations for the effect of parolees on crime, not the other way. I estimate the interaction models using both numbers and days of parolee measures with violent and property crime as the outcome variables. For ease of interpretation, key results are presented in figures.[5] When using numbers of parolee measure, most of the interaction models are not significant, for both violent crime and property crime, except for one – the interaction effect of disadvantage on numbers of parolees and property crime. But there are some interesting findings using days of parolees and I only present the significant effects below. Figure 2 shows the moderating effect of concentrated disadvantage for days of parolees on property crime. When parolees live in the neighborhoods for a short time, it helps decrease the property crime, but neighborhood disadvantage does not have much moderating effect on property crime. However, when parolees live longer in the neighborhoods, the effect of parolees on property crime is quite different for varying levels of disadvantaged neighborhoods. The longer parolees reside in the neighborhoods, the faster the property crime decreases, and this reduction is steepest in high disadvantage neighborhoods. It seems that short-term parolees do not make much difference among good or bad neighborhoods, but long-term parolees are helpful to troubled neighborhoods, i.e. disadvantaged neighborhoods.

[5] In total, I have estimated 12 moderating models, in which I add interaction term of concentrated disadvantage, residential stability, and voluntary organization with numbers of parolees and days of parolees, respectively. Full results of interaction effects are available upon request.

[FIGURE 2 ABOUT HERE]

Figure 3 shows the moderating effect of residential stability on days of parolees and violent crime. The overall pattern of days of parolees' effect on violent crime is decreasing (i.e. negative effect), but the magnitude of the effect varies across different levels of neighborhood stability. When parolees return to neighborhoods with low residential stability, the estimation line is fairly flat, whether parolees stay a short time or long time in the neighborhood, although a slight decrease of violent crime occurs when parolees stay more days there. Instead, when parolees return to neighborhoods with a high level of residential stability, the longer parolees stay in the neighborhoods, the lower the violent crime rate is. Parolees do not exacerbate the violent crime in those highly mobilized or unstable neighborhoods, rather, they largely reduce violent crime in highly stable neighborhoods, if parolees stay longer time in the neighborhoods.

[FIGURE 3 ABOUT HERE]

Lastly, voluntary organizations are an important factor that helps parolees reintegrate into communities and society. My evidence indicates that voluntary organizations moderate the effect of parolees on property crime rates but show little effect for violent crime, and I present this significant moderating effect of voluntary organization on days of parolees and property crime in Figure 4. When parolees return to communities for a short time period, their effect on property crime is not distinguishable for neighborhoods either having small number of organizations or large number. With days parolees staying in the neighborhood longer and longer, the differential effects on property crime emerge for different neighborhoods. Here long-term parolees are associated with a greater decrease in property crime in low voluntary organization neighborhoods compared to high voluntary organization neighborhoods.

[FIGURE 4 ABOUT HERE]

Sensitivity Analyses

My final sets of analyses explore how sensitive my models are in various ways: by splitting the time period in half, and by estimating separate models for each city. First, I estimate the cross-lagged regression models of reciprocal relationships between parolees – numbers and days – and violent crime and property crime for years 2003 to 2007 and for years 2007 to 2011 (see Table A2 in the Appendix for the results of these regression models). Even when I split the time period in half, the results are still consistent with what I see in Table 2A and 2B: no evidence that numbers of parolees living in a neighborhood have any significant effect on violent crime and property crime either the first four-year period or the last four-year period. Turning to the effect of days of parolees on crime, in models from years 2003 to 2007, days of parolees have a marginally significant negative effect on violent crime and the magnitude is -0.016. Regarding the effect of days of parolees on property crime, the coefficients of parolees are both significant and negative either in models for years 2003-2007 or for years 2007-2011. Overall, I see the similar pattern of parolees' effect on crime by separating the whole time period in half.

The final sensitivity analysis I explore is whether the relationship between parolees and crime I observe holds for each city (see Table A3 in the Appendix for results of the regression models). Among these five cities in Texas, the non-significant results of numbers of parolees on violent crime hold for most cities, except for Austin, in which numbers of parolees exhibit a significant negative effect on violent crime (B = -0.003, $p < 0.1$). There is also one exception for numbers of parolees on property crime – Houston, in which numbers of parolees show a significant positive effect on property crime, but the magnitude of the coefficient is small (B = 0.001, $p < 0.01$). When using days of parolees as the key measure, I do not see many significant results, which might be explained by the small number of tracts in each city. I also see a significant positive effect of days of parolees on property crime in Houston (B = 0.011, $p < 0.1$) and Houston has the largest tract number among these five cities. Overall, the patterns I observe above still hold for each city: not many significant relationships between parolees and neighborhood crime, with very few exceptions. However, future research should explore these effects among different cities.

Table 1. Summary statistics for measures used in analyses

Variable	Mean	SD
Key measures		
Violent Crime (per 10,000 population, logged)	3.25	1.59
Property Crime (per 10,000 population, logged)	5.52	1.66
Parolees (counts)	6.59	8.02
Violent Parolees (counts)	1.20	1.78
Drug Parolees (counts)	2.08	2.78
Sex Parolees (counts)	0.15	0.15
Parolees (days, logged)	5.74	2.44
Violent Parolees (days, logged)	2.87	2.85
Drug Parolees (days, logged)	3.78	2.89
Sex Parolees (days, logged)	0.56	1.60
Time invariant measures		
Concentrated disadvantage	0.00	0.10
Residential stability	-0.40	0.74
Gini inequality index	0.40	0.06
Racial/ethnic heterogeneity	0.46	0.17
% immigrants	0.19	0.13
% young people (age 29 or lower)	0.24	0.09
% black	0.18	0.24
% Latino	0.36	0.26
Population density	0.40	0.34
Time varying measures (logged)		
Total enterprises	7.09	1.14
Retail enterprises	4.87	1.44
Recreation enterprises	2.08	1.57
Food enterprises	4.32	1.74
Total number of voluntary organizations	0.61	0.58

Abbreviation: SD = standard deviation.

Table 2A. Reciprocal relationship between number of parolees in a neighborhood and neighborhood crime rates (logged), cross-lagged regression models for Texas, 2003-2011

	Model 1		Model 2	
	Violent crime	Number of parolees	Property crime	Number of parolees
Key measures (all lagged one year)				
Number of parolees	-0.001	0.759***	0.000	0.759***
	(0.000)	(0.006)	(0.000)	(0.006)
Violent crime (logged)	0.965***	-0.006		
	(0.002)	(0.025)		
Property crime (logged)			0.980***	-0.014
			(0.001)	(0.018)
Time invariant measures				
Concentrated disadvantage	0.083†	3.124***	-0.087*	3.035***
	(0.047)	(0.593)	(0.042)	(0.597)
Residential stability	-0.013**	0.170**	-0.011*	0.164**
	(0.005)	(0.058)	(0.004)	(0.059)
Gini inequality	0.022	-0.729	0.068†	-0.671
	(0.041)	(0.519)	(0.036)	(0.511)
Racial/ethnic heterogeneity	0.039**	0.105	0.046***	0.109
	(0.015)	(0.182)	(0.013)	(0.182)
% Immigrants	-0.079**	-1.099***	-0.285***	-1.163***
	(0.025)	(0.308)	(0.022)	(0.305)
% Young age in neigh.	-0.037	-0.812†	-0.030	-0.799†
	(0.033)	(0.435)	(0.030)	(0.437)
% Black	0.098***	2.484***	0.018	2.504***
	(0.018)	(0.225)	(0.015)	(0.216)
% Latinos	0.104***	0.979***	0.164***	1.031***
	(0.018)	(0.224)	(0.016)	(0.227)
Population density	0.013†	0.174†	0.003	0.181†
	(0.008)	(0.094)	(0.007)	(0.093)
Time varying measures (lagged one year and logged)				
Total enterprises	0.009**	0.071	0.004	0.074†
	(0.004)	(0.044)	(0.003)	(0.044)
Retail enterprises	-0.004	0.002	0.001	0.003
	(0.003)	(0.033)	(0.002)	(0.033)
Recreation enterprises	-0.000	0.031	-0.002	0.030
	(0.002)	(0.020)	(0.002)	(0.020)
Food enterprises	-0.000	0.009	-0.001	0.009
	(0.002)	(0.024)	(0.002)	(0.024)
Voluntary organizations	0.009*	0.214***	0.005	0.214***
	(0.004)	(0.050)	(0.004)	(0.050)
Goodness of fit				
RMSEA	0.032		0.035	
CFI	0.970		0.971	
TLI	0.968		0.969	
N	1,613			

Standard errors in parentheses
† p<.10, * p<.05, ** p<.01, *** p<.001

Table 2B. Reciprocal relationship between days of parolees in a neighborhood (logged) and neighborhood crime rates (logged), cross-lagged regression models for Texas, 2003-2011

	Model 1		Model 2	
	Violent crime	Days of parolees	Property crime	Days of parolees
Key measures (all lagged one year and logged)				
Days of parolees	-0.003†	0.833***	-0.005***	0.831***
	(0.002)	(0.007)	(0.001)	(0.007)
Violent crime	0.965***	-0.011		
	(0.002)	(0.007)		
Property crime			0.980***	-0.014**
			(0.001)	(0.005)
Time invariant measures				
Concentrated disadvantage	0.119*	2.113***	-0.017	2.059***
	(0.051)	(0.170)	(0.044)	(0.170)
Residential stability	-0.013**	0.061***	-0.008†	0.057***
	(0.005)	(0.015)	(0.004)	(0.015)
Gini inequality	0.017	-0.811***	0.059	-0.813***
	(0.041)	(0.130)	(0.036)	(0.127)
Racial/ethnic heterogeneity	0.043**	0.260***	0.055***	0.272***
	(0.015)	(0.046)	(0.013)	(0.046)
% Immigrants	-0.075**	-0.166*	-0.285***	-0.237**
	(0.025)	(0.076)	(0.022)	(0.076)
% Young age in neigh.	-0.047	-0.604***	-0.046	-0.607***
	(0.033)	(0.110)	(0.030)	(0.111)
% Black	0.096***	0.463***	0.028*	0.466***
	(0.017)	(0.053)	(0.014)	(0.051)
% Latinos	0.102***	0.194***	0.167***	0.237***
	(0.018)	(0.055)	(0.016)	(0.056)
Population density	0.015†	0.059*	0.006	0.064**
	(0.008)	(0.024)	(0.007)	(0.023)
Time varying measures (lagged one year and logged)				
Total enterprises	0.009*	0.011	0.004	0.013
	(0.004)	(0.011)	(0.003)	(0.011)
Retail enterprises	-0.004	0.008	0.001	0.008
	(0.003)	(0.009)	(0.002)	(0.009)
Recreation enterprises	-0.000	0.014*	-0.002	0.014*
	(0.002)	(0.006)	(0.001)	(0.006)
Food enterprises	0.000	0.017**	-0.001	0.017**
	(0.002)	(0.006)	(0.002)	(0.006)
Voluntary organizations	0.009*	0.026*	0.006†	0.026*
	(0.004)	(0.012)	(0.004)	(0.012)
Goodness of fit				
RMSEA	0.018		0.024	
CFI	0.990		0.987	
TLI	0.990		0.986	
N	1,613			

Standard errors in parentheses
† p<.10, * p<.05, ** p<.01, *** p<.001

Table 3A. Reciprocal relationship between different types of parolees in a neighborhood (counts) and neighborhood crime rates (logged), cross-lagged regression models for Texas, 2003-2011

Panel A: reciprocal relationship between parolees and violent crime rates

	Model 1		Model 2		Model 3	
	Violent crime	Violent parolees	Violent crime	Drug parolees	Violent crime	Sex parolees
Key measures (all lagged one year)						
Number of violent parolees	0.000 (0.002)	0.716*** (0.007)				
Number of drug parolees			-0.001 (0.001)	0.712*** (0.001)		
Number of sex parolees					0.000 (0.005)	0.668*** (0.006)
Violent crime (logged)	0.965*** (0.002)	-0.013* (0.006)	0.965*** (0.002)	0.002 (0.008)	0.965*** (0.002)	0.003 (0.003)
Goodness of fit						
RMSEA	0.019		0.022		0.024	
CFI	0.986		0.984		0.976	
TLI	0.985		0.983		0.975	
N			1,613			

Panel B: reciprocal relationship between parolees and property crime rates

	Model 4		Model 5		Model 6	
	Property crime	Violent parolees	Property crime	Drug parolees	Property crime	Sex parolees
Key measures (all lagged one year)						
Number of violent parolees	0.000 (0.000)	0.716*** (0.007)				
Number of drug parolees			0.000 (0.000)	0.712*** (0.006)		
Number of sex parolees					0.002 (0.004)	0.668*** (0.006)
Property crime (logged)	0.980*** (0.001)	-0.011* (0.004)	0.980*** (0.001)	-0.002 (0.006)	0.980*** (0.001)	0.003 (0.002)
Goodness of fit						
RMSEA	0.024		0.026		0.028	
CFI	0.983		0.982		0.976	
TLI	0.982		0.981		0.974	
N			1,613			

Standard errors in parentheses
† $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 3B. Reciprocal relationship between different types of parolees in a neighborhood (days) and neighborhood crime rates (logged), cross-lagged regression models for Texas, 2003-2011

Panel A: reciprocal relationship between parolees and violent crime rates

	Model 1		Model 2		Model 3	
	Violent crime	Violent parolees	Violent crime	Drug parolees	Violent crime	Sex parolees
Key measures (all lagged one year and logged)						
Days of violent parolees	0.000 (0.001)	0.732*** (0.009)				
Days of drug parolees			-0.004** (0.001)	0.760*** (0.009)		
Days of sex parolees					-0.000 (0.002)	0.676*** (0.008)
Violent crime	0.965*** (0.002)	-0.027** (0.010)	0.965*** (0.002)	0.003 (0.010)	0.965*** (0.002)	0.007 (0.007)
Goodness of fit						
RMSEA	0.017		0.016		0.016	
CFI	0.990		0.991		0.989	
TLI	0.989		0.990		0.988	
N			1,613			

Panel B: reciprocal relationship between parolees and property crime rates

	Model 4		Model 5		Model 6	
	Property crime	Violent parolees	Property crime	Drug parolees	Property crime	Sex parolees
Key measures (all lagged one year and logged)						
Days of violent parolees	-0.002* (0.001)	0.730*** (0.009)				
Days of drug parolees			-0.005*** (0.001)	0.759*** (0.009)		
Days of sex parolees					-0.001 (0.001)	0.676*** (0.008)
Property crime	0.980*** (0.001)	-0.028*** (0.007)	0.980*** (0.001)	-0.000 (0.007)	0.980*** (0.001)	0.008† (0.005)
Goodness of fit						
RMSEA	0.022		0.022		0.022	
CFI	0.986		0.987		0.985	
TLI	0.985		0.987		0.985	
N			1,613			

Standard errors in parentheses
† $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Figure 2. Moderating effect of concentrated disadvantage on days of parolees in a neighborhood and neighborhood property crime

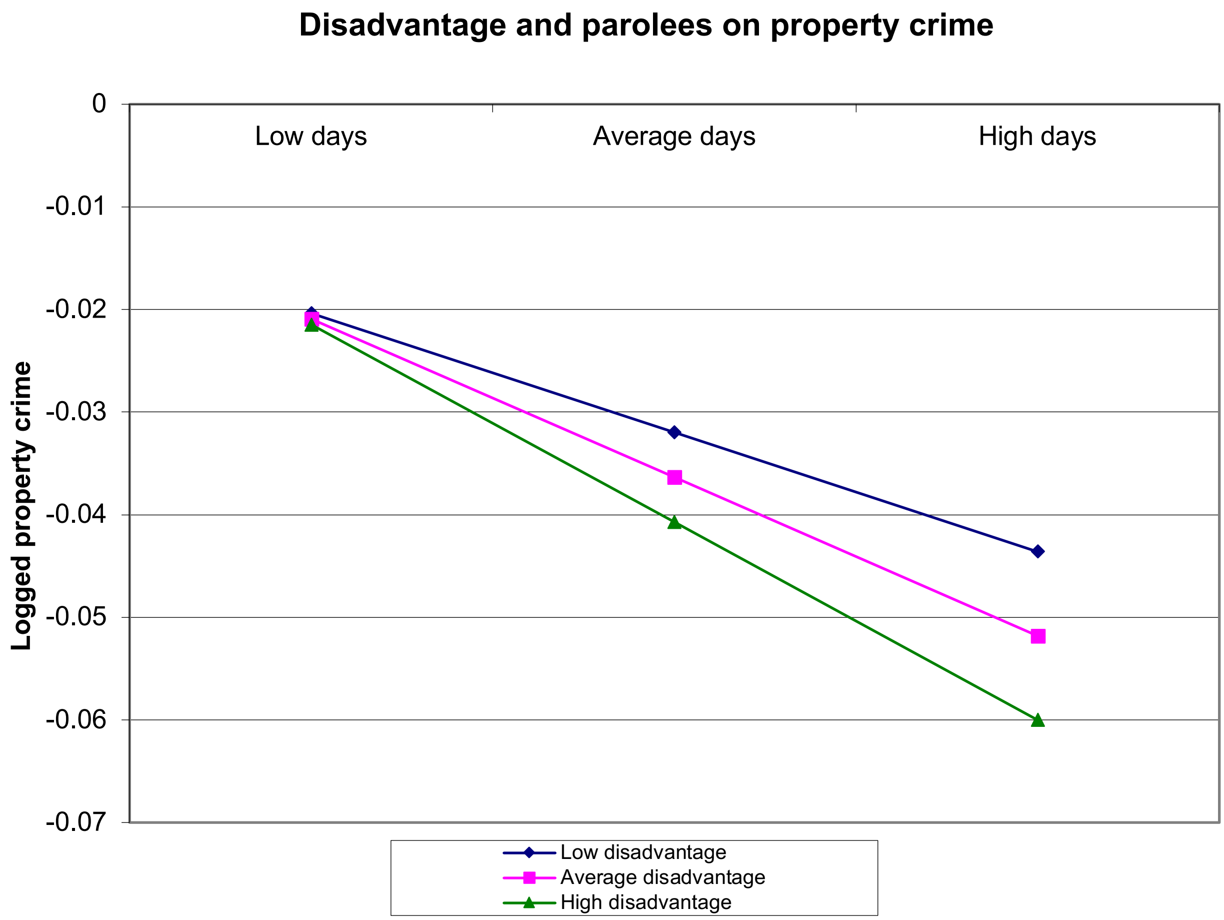


Figure 3. Moderating effect of residential stability on days of parolees in a neighborhood and neighborhood violent crime

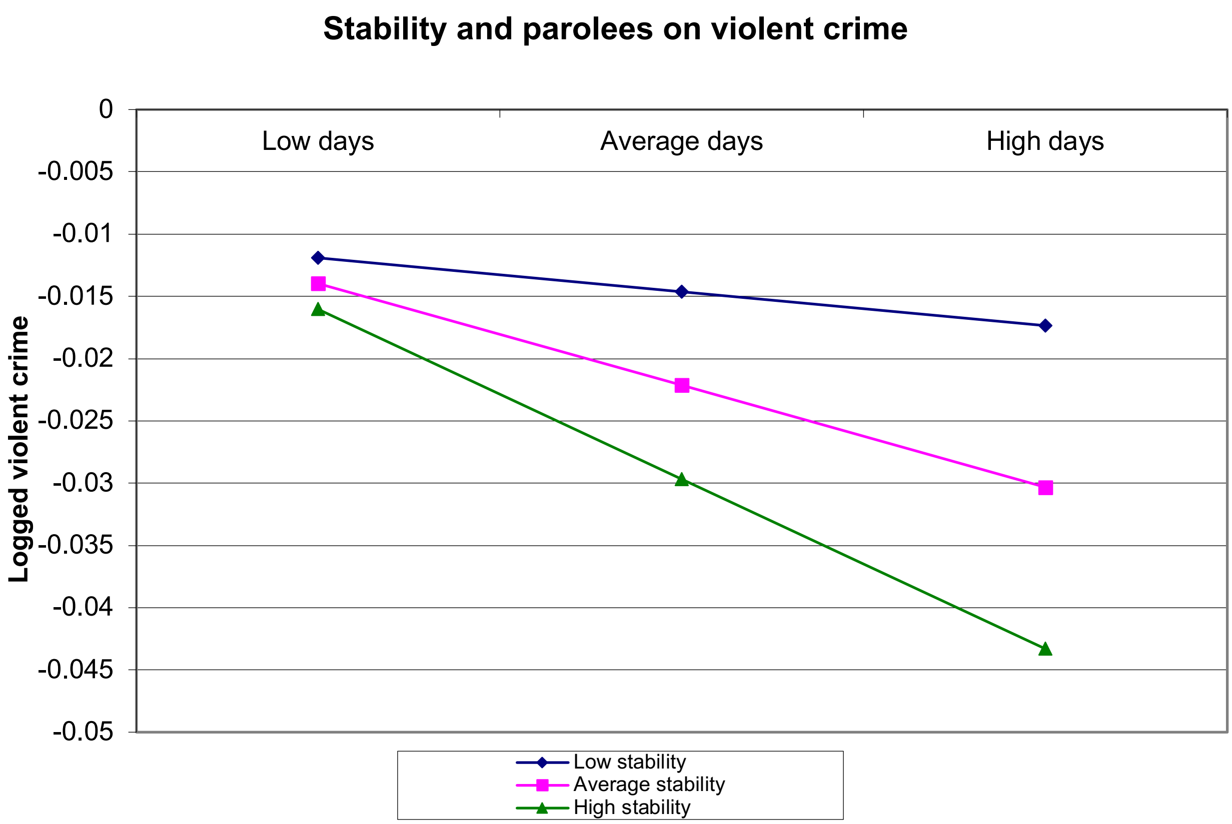
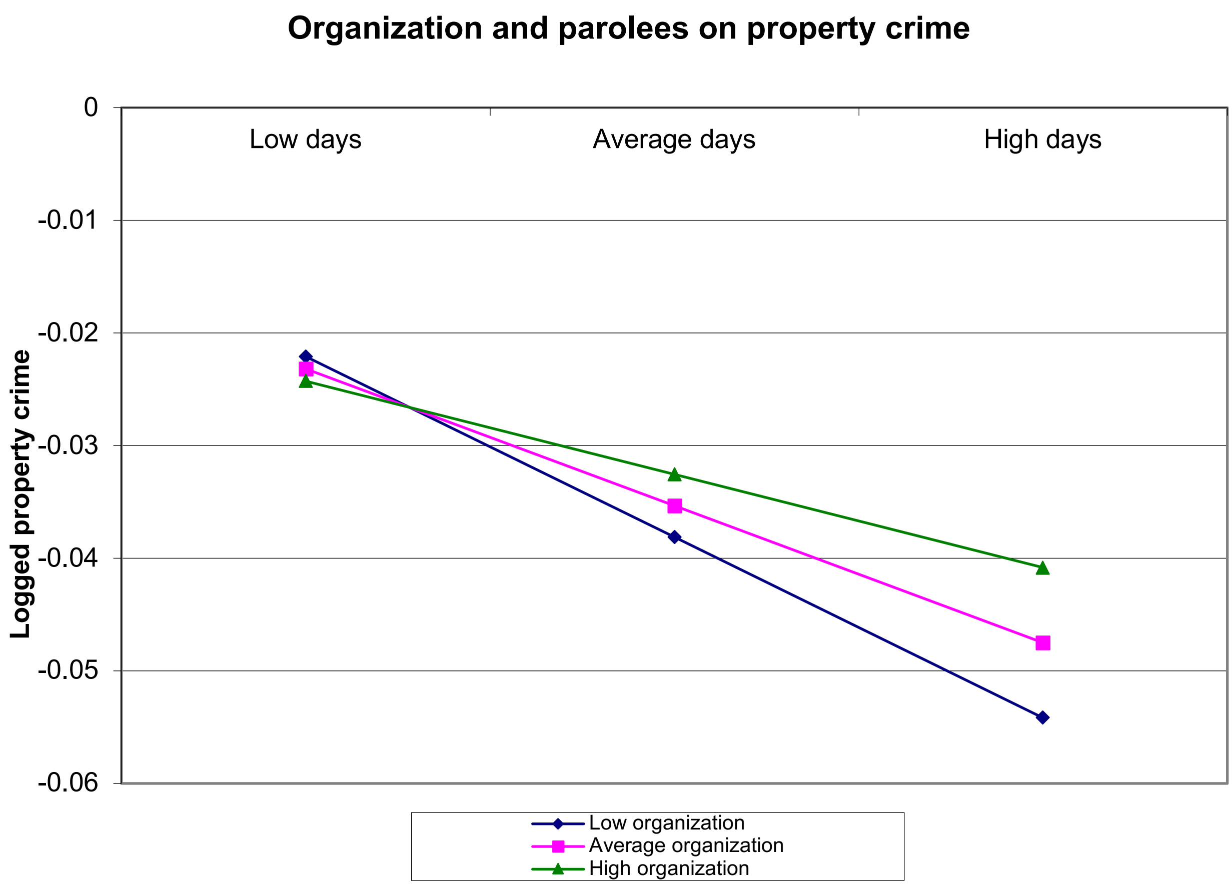


Figure 4. Moderating effect of voluntary organization on days of parolees in a neighborhood and neighborhood property crime



CHAPTER 5: DISCUSSION AND CONCLUSION

Although recent scholarship has noted a decreasing trend of crime rates in the U.S. since the 1990s, the accumulated prison population is still massive and there is an increasing number of prisoners being released back to communities. Scholars are interested in how returning parolees might affect neighborhoods as a whole and neighborhood crime rates in particular. This study extends the research of parolees and neighborhood crime by examining their reciprocal relationship. Most importantly, I test a new approach of measuring parolees – the time parolees actually stay in the neighborhoods – to explore this reciprocal relationship. Key findings are discussed below.

Overall, my study provides robust evidence that the effect of parolees on neighborhood crime depends on how researchers measure parolees at the neighborhood level. I find no evidence that number of parolees living in a neighborhood in one year has any significant effect on either violent or property crime rates the following year, which contradicts findings from some previous research (Chamberlain 2016, Hipp and Yates 2009). Several studies have reached a consistent finding that number of parolees in a neighborhood increase the rate of crime for several cities or counties, such as Sacramento (Hipp and Yates 2009), Cleveland (Chamberlain 2016, Chamberlain and Boggess 2018), Seattle (Drakulich et al. 2012), Multnomah County, Oregon (Kubrin and Stewart 2006). These studies on parolees and crime are based on cities or county within different states, including California, Ohio, Michigan, Washington, and Oregon. It is interesting to note that there is no evidence in these five Texas cities captured here – Austin, Dallas, Fort Worth, Houston, and San Antonio – that parolees returning to communities result in increased neighborhood crime rates. This may suggest that state-level context matters, as the impact of prison releases on crime differs across different state-level parole systems (Raphael and Stoll 2004) and states in the sunbelt region such as Texas may be distinct for states in the American West (Lynch 2009).

Another central finding of this study is that neighborhood with people who spend more time in their neighborhood (i.e., longer exposure) is associated with both violent crime rates and property crime rates. One percent increase in the days of yearly parolees in the former year is expected to decrease the violent crime rates by 0.3 percent and the property crime rates by 0.5 percent in the next year. This negative relationship suggests that parolees returning to and staying in the communities can actually help reduce the neighborhood crime. If parolees stay in the neighborhood longer, it is possible that they are more likely to integrate into communities and society and return back to a prosocial life trajectory, which can help build strong informal social control in the neighborhood and further decrease neighborhood crime rates. These communities may tend to be those with stronger economic strength and able to absorb parolees, which implies that the relationship between prisoner reentry and crime is substantially lessened by strong economic conditions (Hannon and DeFina 2014). Some other possible reason of this negative relationship might be that the neighborhoods where parolees return are economically damaged, which lower the possibilities of potential offenders committing property crime. Still, more research is needed for understanding the dynamic relationship between parolees and crime.

Another key finding is that my two measures of neighborhoods with people on parole -numbers of parolees and days of parolees - are evidence of a strong selection effect of parolees in the neighborhood. The effect of parolees on neighborhood crime is likely biased when I count parolees as the number of days each parolee stays in a neighborhood. It is possible that parolees who stay in the neighborhood longer are those ex-offenders who are less likely to commit crime again and have low recidivism rate, thus they are weighted more in the analyses than those who stay shorter time and are back to prison quickly when I capture days of parolees. It is important to consider neighborhoods' exposure to parolees, but it can also overestimate the pro-social parolees' effect on crime.

When examining the characteristics of parolees and how they may differentially affect neighborhood crime, the results concerning number of parolees and crime are still not significant, and it does not matter what type of offenses parolees have committed before. The only significant effects I detect are when I measure the types of parolees based on the days they spent in the neighborhood. Surprisingly, with returning drug offense parolees residing in neighborhoods longer, a lower level of violent crime rates occurs in the neighborhood. It may be difficult for returning parolees to rebuild social networks in a short time period. Consequently, there is a reduced pool of motivated offenders, which may contribute to the decrease of violent crime rates. In addition, research shows that reincarceration rates are positively associated with the concentration of parolees (Kirk 2015). Parolees clustering in more dispersed neighborhoods may also help explain the lower level of violent crime rates in the neighborhoods, but I am not able to accurately capture parolees' residential mobility using the current data. In terms of property crime rates, there is a decreasing trend in neighborhoods with longer-term violent offense parolees and drug offense parolees residing there. Due to the stigmatization of parolees and felony criminal records (Raphael and Stoll 2004), and the perceptions of these neighborhoods as “bad places”, businesses that might provide jobs are reluctant to locate in these neighborhoods. The loss of business investment in those neighborhoods, and parolees’ negative influence on the income at the neighborhood level may help explain the decrease of property crime rates in the neighborhood.

Further, the moderating effect of neighborhood characteristics on days of parolees and property crime needs discussion. I find that returning parolees decrease the rate of property crime in neighborhoods, surprisingly, this effect is amplified in neighborhoods with higher levels of concentrated disadvantages. For low levels of structural disadvantaged neighborhoods, there may be not much room left for crime reduction as one possible reason being that it has already reached a saturated crime rate (Krivo and Peterson 2000), and this balance is hard to break even with long-term parolees retuning to these neighborhoods. In addition, drawn from social disorganization perspective, socially organized neighborhoods have strong informal social control. As expected, the significantly negative effect of days of parolees on violent crime is stronger in neighborhoods with higher level of residential stability. Returning parolees can also be a positive force in families when parolees live longer in neighborhoods with low residential stability. Despite some illuminating findings, new thinking and empirical analyses are demanded to gain better understanding of the reasons of these sometimes surprising moderating effects.

Despite the uniqueness of my data and the importance of my findings, certain limitations deserve to be acknowledged. Returning parolees disproportionately cluster in poor urban communities (Clear 2009, Morenoff and Harding 2014). For the present study, parolees were tracked to their current address after release from prison, however, I do not have the information of where parolees lived before they were sent to prison. Due to this data limitation, I cannot tell whether parolees cluster in neighborhoods where they used to live, or if they are more geographically dispersed. Another limitation of the current study is that I am not able to include a measure of incarceration rate of a neighborhood. There is increasing research on the connection between incarceration and social inequality (Clear 2009, Sykes and Maroto 2016), including household assets, debt, employment, etc. Incarceration also disrupts the informal social control of the neighborhoods by removing people from their communities. Parolees may be more likely to return to neighborhoods with higher incarceration rates. This social process of incarceration may exert a confounding effect on neighborhood crime, net of returning parolees.

Despite these limitations, my research advances the understanding of prison reentry and neighborhood crime across multiple dimensions. I decompose the reciprocal effect of parolees on neighborhood crime and the effect of crime on parolees. Moreover, I advance the literature of parolees and neighborhood crime by examining the actual time parolees stay in the communities and how it has shaped the dynamics of parolee reentry and neighborhood crime. Although my new approach of measuring parolees may not be a better way to tackle this relationship, as I have shown the strong selection effect of days of parolees in my analyses, it does propose a new way to think about the neighborhood and parolee process.

With large populations of ex-offenders returning to free society, public safety and crime control are often the top priority among political actors, while the broader impact that parolees may have on neighborhood crime is under addressed empirically and practically. As a crucial component of society, neighborhoods and communities are places which have the most connection with parolees' reintegration. Understanding the extent to which parolees may impact or are impacted by communities is the first step for beginning the collaboration among community members, institutions, and the criminal justice system to create an environment tailored for successful reintegration. Especially, neighborhood context really matters in prisoner reentry as the social, economic, and institutional processes that sort formerly incarcerated people into different neighborhoods after release vary across neighborhoods and over time (Lee, Harding and Morenoff 2017, Simes 2018). I highlight the dynamics of parolee reentry and neighborhood crime in the era of mass incarceration to provide insights for policy initiatives.

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APPENDIX

Table A1. Summary statistics for parolees and crime

Year	Parolees (counts)				Parolees (days, logged)				Crime (per 10,000 population, logged)	
	Parolees	Violent parolees	Drug parolees	Sex parolees	Parolees	Violent parolees	Drug parolees	Sex parolees	Violent crime	Property crime
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
2003	9.17	1.81	3.60	0.23	6.53	3.72	4.93	0.87	3.31	5.53
	(11.06)	(2.59)	(4.65)	(0.81)	(2.40)	(3.12)	(2.98)	(2.05)	(1.64)	(1.71)
2004	7.82	1.61	2.98	0.21	6.24	3.52	4.52	0.82	3.31	5.54
	(10.72)	(2.40)	(4.12)	(0.74)	(2.50)	(3.09)	(3.06)	(1.97)	(1.63)	(1.69)
2005	5.94	1.16	2.06	0.13	5.65	2.89	3.87	0.57	3.29	5.51
	(6.94)	(1.69)	(2.74)	(0.47)	(2.62)	(2.94)	(3.00)	(1.66)	(1.64)	(1.70)
2006	6.21	1.11	2.03	0.14	5.68	2.77	3.84	0.54	3.23	5.45
	(7.20)	(1.68)	(2.67)	(0.44)	(2.44)	(2.87)	(2.91)	(1.61)	(1.62)	(1.68)
2007	5.94	0.96	1.81	0.12	5.61	2.52	3.67	0.43	3.30	5.53
	(7.03)	(1.52)	(2.40)	(0.44)	(2.39)	(2.79)	(2.85)	(1.41)	(1.59)	(1.66)
2008	6.06	0.98	1.75	0.13	5.59	2.59	3.57	0.47	3.24	5.49
	(7.33)	(1.46)	(2.34)	(0.56)	(2.35)	(2.73)	(2.80)	(1.47)	(1.60)	(1.61)
2009	6.31	1.04	1.67	0.11	5.55	2.58	3.39	0.37	3.23	5.59
	(8.22)	(1.60)	(2.37)	(0.52)	(2.36)	(2.71)	(2.81)	(1.31)	(1.60)	(1.67)
2010	5.93	1.00	1.42	0.15	5.38	2.51	3.14	0.44	3.23	5.54
	(7.05)	(1.51)	(1.87)	(0.69)	(2.44)	(2.69)	(2.78)	(1.40)	(1.53)	(1.64)
2011	5.97	1.10	1.40	0.16	5.41	2.71	3.09	0.52	3.10	5.48
	(6.61)	(1.53)	(1.82)	(0.55)	(2.42)	(2.67)	(2.77)	(1.52)	(1.52)	(1.59)

Table A2. Reciprocal relationship between parolees and crime rates (logged), cross-lagged regression models for Texas

Panel A: reciprocal relationship between numbers of parolees and crime rates

	Year 2003-2007				Year 2007-2011			
	Model 1		Model 2		Model 3		Model 4	
	Violent crime	Number of parolees	Property crime	Number of parolees	Violent crime	Number of parolees	Property crime	Number of parolees
Number of parolees (lag)	-0.001	0.760***	0.000	0.760***	0.000	0.815***	-0.001	0.814***
	(0.001)	(0.006)	(0.000)	(0.006)	(0.001)	(0.010)	(0.001)	(0.011)
Violent crime (lag, logged)	0.940***	0.014			0.950***	-0.026		
	(0.004)	(0.033)			(0.004)	(0.034)		
Property crime (lag, logged)			0.982***	0.008			0.972***	-0.034
			(0.002)	(0.024)			(0.002)	(0.025)
Concentrated disadvantage	0.001	0.016*	-0.001	0.016*	0.002*	0.036***	-0.000	0.034***
	(0.001)	(0.008)	(0.001)	(0.008)	(0.001)	(0.008)	(0.001)	(0.008)
Residential stability	-0.010	0.067	-0.003	0.067	-0.015†	0.220**	-0.016*	0.216**
	(0.009)	(0.078)	(0.006)	(0.078)	(0.009)	(0.079)	(0.008)	(0.079)
Gini inequality	0.003***	-0.005	0.001**	-0.005	0.000	-0.011	0.000	-0.010
	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)
Racial/ethnic heterogeneity	0.000	0.002	0.000	0.001	0.000	0.001	0.001**	0.002
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)
% immigrants	-0.000	-0.012**	-0.002***	-0.012**	-0.001*	-0.009*	-0.004***	-0.010*
	(0.000)	(0.004)	(0.000)	(0.004)	(0.000)	(0.004)	(0.000)	(0.004)
% young age	-0.000	-0.008	0.000	-0.008	-0.001	-0.005	-0.001	-0.005
	(0.001)	(0.006)	(0.000)	(0.006)	(0.001)	(0.006)	(0.001)	(0.006)
% black	0.002***	0.018***	0.000	0.018***	0.001†	0.027***	0.000	0.027***
	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)
% Latinos	0.002***	0.011***	0.001***	0.011***	0.001†	0.008*	0.002***	0.009**
	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)
Population density	0.002†	0.017	-0.001	0.017	0.003*	0.010	0.003*	0.010
	(0.001)	(0.012)	(0.001)	(0.012)	(0.001)	(0.013)	(0.001)	(0.013)
Number of employees (total)	0.008	0.063	0.003	0.064	0.021**	0.080	0.007	0.084
	(0.007)	(0.058)	(0.005)	(0.058)	(0.007)	(0.059)	(0.006)	(0.059)
Number of employees (retail)	0.002	-0.002	0.001	-0.003	-0.011*	-0.022	0.003	-0.022
	(0.005)	(0.044)	(0.003)	(0.044)	(0.005)	(0.044)	(0.004)	(0.044)
Number of employees (recre.)	-0.003	0.025	-0.002	0.025	0.002	0.037	-0.000	0.030
	(0.003)	(0.027)	(0.002)	(0.027)	(0.003)	(0.034)	(0.003)	(0.027)
Number of employees (food)	0.005	-0.005	-0.001	-0.003	-0.004	0.175**	-0.003	0.037
	(0.004)	(0.031)	(0.002)	(0.031)	(0.004)	(0.067)	(0.003)	(0.034)
Number of voluntary org.	0.014†	0.162*	0.008	0.162*	0.004	0.030	0.003	0.174**
	(0.008)	(0.068)	(0.005)	(0.068)	(0.008)	(0.027)	(0.006)	(0.067)
N	1,613							

Standard errors in parentheses
† p<.10, * p<.05, ** p<.01, *** p<.001

Panel B: reciprocal relationship between days of parolees and crime rates

	Year 2003-2007				Year 2007-2011			
	Model 1		Model 2		Model 3		Model 4	
	Violent crime	Days of parolees	Property crime	Days of parolees	Violent crime	Days of parolees	Property crime	Days of parolees
Days of parolees	-0.016†	0.830***	-0.011†	0.831***	-0.010	0.774***	-0.030***	0.771***
(lag, logged)	(0.008)	(0.006)	(0.006)	(0.006)	(0.011)	(0.010)	(0.008)	(0.010)
Violent crime	0.940***	-0.001			0.950***	-0.006*		
(lag, logged)	(0.004)	(0.003)			(0.004)	(0.003)		
Property crime			0.982***	0.001			0.972***	-0.008***
(lag, logged)			(0.002)	(0.002)			(0.002)	(0.002)
Concentrated	0.001	0.003***	-0.000	0.003***	0.002**	0.006***	0.000	0.006***
disadvantage	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Residential	-0.009	0.019**	0.001	0.018**	-0.013	0.026***	-0.011	0.025***
stability	(0.009)	(0.007)	(0.006)	(0.007)	(0.009)	(0.007)	(0.008)	(0.007)
Gini inequality	0.003***	-0.001*	0.001**	-0.001*	0.000	-0.002**	0.000	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Racial/ethnic	0.000†	-0.000	0.000	-0.000	0.000	0.001**	0.001***	0.001**
heterogeneity	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% immigrants	0.000	-0.000	-0.002***	-0.000	-0.001*	-0.001*	-0.004***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% young age	-0.000	-0.000	0.000	-0.001	-0.001	-0.001*	-0.001	-0.001*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
% black	0.002***	0.002***	0.001*	0.002***	0.001*	0.003***	0.000†	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Latinos	0.002***	0.000	0.001***	0.000	0.001†	0.001**	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	0.003†	0.001	-0.000	0.001	0.003*	0.002	0.003*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of	0.008	0.005	0.004	0.005	0.021**	0.004	0.007	0.005
employees (total)	(0.007)	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)
Number of	0.002	0.001	0.001	0.001	-0.011*	-0.000	0.003	-0.000
employees (retail)	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Number of	-0.003	0.004	-0.002	0.004†	0.002	0.001	-0.000	0.007*
employees (recre.)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Number of	0.005	0.001	-0.001	0.001	-0.004	0.007*	-0.003	0.018**
employees (food)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.006)
Number of	0.015†	0.015**	0.009†	0.015**	0.005	0.018**	0.005	0.001
voluntary org.	(0.008)	(0.006)	(0.005)	(0.006)	(0.008)	(0.006)	(0.006)	(0.003)
N				1,613				

Standard errors in parentheses
† p<.10, * p<.05, ** p<.01, *** p<.001

Table A3. Reciprocal relationship between parolees and crime rates by city, cross-lagged regression models for Texas

Panel A: numbers of parolees and violent crime by city

	Austin		Dallas		Fort Worth		Houston		San Antonio	
	Violent crime	Num. of parolees	Violent crime	Num. of parolees	Violent crime	Num. of parolees	Violent crime	Num. of parolees	Violent crime	Num. of parolees
Numbers of parolees (lag)	-0.003*	0.865***	-0.001	0.812***	-0.003†	0.744***	0.001	0.737***	0.002	0.807***
	(0.002)	(0.015)	(0.001)	(0.011)	(0.001)	(0.018)	(0.000)	(0.009)	(0.002)	(0.012)
Violent crime (lag, logged)	0.931***	-0.053	0.949***	-0.061	0.934***	-0.132	0.989***	-0.025	0.924***	0.064
	(0.010)	(0.062)	(0.005)	(0.050)	(0.012)	(0.103)	(0.002)	(0.037)	(0.011)	(0.046)
N	205		316		168		600		324	

Panel B: days of parolees and violent crime by city

	Austin		Dallas		Fort Worth		Houston		San Antonio	
	Violent crime	Days of parolees	Violent crime	Days of parolees	Violent crime	Days of parolees	Violent crime	Days of parolees	Violent crime	Days of parolees
Days of parolees (lag, logged)	-0.017	0.818***	-0.002	0.863***	-0.031†	0.849***	-0.001	0.855***	0.023	0.818***
	(0.018)	(0.014)	(0.010)	(0.010)	(0.018)	(0.017)	(0.006)	(0.008)	(0.016)	(0.012)
Violent crime (lag, logged)	0.935***	-0.004	0.949***	-0.004	0.936***	-0.019*	0.989***	-0.003	0.925***	0.010†
	(0.010)	(0.006)	(0.005)	(0.004)	(0.012)	(0.008)	(0.002)	(0.002)	(0.011)	(0.006)
N	205		316		168		600		324	

Panel C: numbers of parolees and property crime by city

	Austin		Dallas		Fort Worth		Houston		San Antonio	
	Property crime	Num. of parolees	Property crime	Num. of parolees	Property crime	Num. of parolees	Property crime	Num. of parolees	Property crime	Num. of parolees
Number of parolees (lag)	-0.001	0.863***	-0.000	0.811***	-0.001	0.740***	0.001**	0.737***	-0.000	0.806***
	(0.001)	(0.015)	(0.001)	(0.011)	(0.001)	(0.018)	(0.000)	(0.009)	(0.002)	(0.012)
Property crime (lag, logged)	0.968***	-0.021	0.979***	-0.042	0.971***	-0.110	0.995***	-0.001	0.931***	-0.001
	(0.006)	(0.044)	(0.003)	(0.046)	(0.005)	(0.070)	(0.001)	(0.027)	(0.007)	(0.033)
N	205		316		168		600		324	

Panel D: days of parolees and property crime by city

	Austin		Dallas		Fort Worth		Houston		San Antonio	
	Property crime	Days of parolees	Property crime	Days of parolees	Property crime	Days of parolees	Property crime	Days of parolees	Property crime	Days of parolees
Days of parolees (lag, logged)	-0.017	0.820***	-0.011†	0.862***	-0.033*	0.847***	0.011*	0.855***	-0.016	0.818***
	(0.014)	(0.014)	(0.006)	(0.010)	(0.013)	(0.017)	(0.005)	(0.008)	(0.014)	(0.012)
Property crime (lag, logged)	0.968***	-0.005	0.979***	-0.004	0.970***	-0.010†	0.995***	-0.001	0.932***	0.002
	(0.006)	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.001)	(0.002)	(0.007)	(0.004)
N	205		316		168		600		324	

Standard errors in parentheses
† p<.10, * p<.05, ** p<.01, *** p<.001