Title
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Journal
Journal of Quantitative Criminology, 38(3)

ISSN
0748-4518

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Publication Date
2022-09-01

DOI
10.1007/s10940-021-09510-z

Peer reviewed

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February 19, 2021

Post-print. Published in Journal of Quantitative Criminology online

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**The network of neighborhoods and geographic space:
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Abstract

Objectives: Few studies have examined the consequences of neighborhoods for job prospects for people on parole. Specifically, networks between neighborhoods in where people commute to work and their spatial distributions may provide insight into patterns of joblessness because they represent the economic structure between neighborhoods. We argue that the network of neighborhoods provides insight into the competition people on parole face in the labor market, their spatial mismatch from jobs, as well as their structural support.

Methods: We use data from people on parole released in Texas from 2006 to 2010 and create a network between all census tracts in Texas based on commuting ties from home to work. We estimate a series of multilevel models examining how network structures are related to joblessness.

Results: The findings indicate that the structural position of neighborhoods has consequences for people on parole's joblessness. Higher outdegree, reflecting neighborhoods with more outgoing ties to other neighborhoods, was consistently associated with less joblessness, while higher indegree, reflecting neighborhoods with more incoming ties into the neighborhood, was associated with more joblessness, particularly for Black and Latino people on parole. There was also some evidence of differences depending on geographic scale.

Conclusions: Structural neighborhood-to-neighborhood networks are another component to understanding joblessness while people are on parole. The most consistent support was shown for the competition and structural support mechanisms, rather than spatial mismatch.

Keywords: neighborhoods, networks, spatial effects, parole, joblessness

Bio

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Acknowledgements: We thank Marisa Omori for her input on an earlier draft of this paper.

The network of neighborhoods and geographic space:

Implications for joblessness while on parole

Scholars have examined the employment patterns of individuals on parole for decades, in a large part because unemployment is linked with recidivism and other detrimental outcomes (National Research Council 2014). Several studies have documented the challenges that individuals on parole face when entering the job market, including stigma, labeling, and an unwillingness of employers in hiring them (Apel and Sweeten 2010, Pager and Quillian 2005, Pager 2007, Petersilia 2003, Pettit and Lyons 2007, Sugie 2020, Quillian et al. 2020). While most studies examine people on parole or potential employer characteristics, only a few studies have examined the neighborhood context of individuals on parole. Neighborhood context is likely consequential for parole (Kubrin and Stewart 2006), but no studies of which we are aware have examined the role of the broader context of neighborhood to neighborhood networks. In this paper, we consider the structural and spatial neighborhood context of people on parole.

One key consideration for our project focuses on the structural position of a neighborhood. Sampson (2012, p. 327) argues for considering the network of neighborhoods through the structural interconnections between neighborhoods. As such, it is not simply the characteristics of the neighborhood where people on parole live that matters, but also how their neighborhood is structurally positioned *relative* to other neighborhoods in the broader environment. In this study, we define the structural links between neighborhoods based on the observed employment patterns in the labor market (i.e., commute flows). In doing so, we capture the economic structure in which people on parole are embedded, and how this structure has consequences for finding a job. Accordingly, commuting flows between neighborhoods represent economic links between neighborhoods (see also Graif et al. 2017, 2019, Kelling et al. 2020), and by examining the structure of these links, we capture how the neighborhood of a person on parole is (or is not) integrated into the labor market. Somewhat similarly, another related line of research focuses on the activity space of people whereby their activity and commuting patterns result in ties between neighborhoods (Browning et al. 2017; Wang et al. 2019), suggesting that these activity patterns may have consequences for joblessness (e.g., awareness of job openings). We argue that this form of tie based on commuting is particularly appropriate for understanding how interlinkages between neighborhoods can affect the employment prospects of people on parole given that they can provide information about potential employment.

One issue for studies examining networks of neighborhoods is that the ties between neighborhoods may have differing consequences depending on their spatial scale. While scholars are increasingly considering processes outside of the local residential area, classic urban sociology work from Hunter (1985) and Fischer (1982) suggests that multiple spatial scales (i.e., the micro neighborhood, the meso area nearby the neighborhood, and a more macro scale) are all potentially relevant for local neighborhood processes and may not operate in the same way. More recently, Morenoff and Harding (2011) show that different spatial scales—the local tract disadvantage and the county unemployment rate—both have consequences for a parolee's job prospects, suggesting a need to consider varying spatial scales. Following the general suggestion of Hipp and Williams (2020) to explicitly incorporate spatial patterns into criminology, in this study we examine how the spatial scale of the structure of the ties between neighborhoods (based on commuting patterns) has differing consequences for joblessness while on parole.

While the vast majority of prior neighborhood research for people returning home from prison has focused on recidivism (Berg and Huebner 2011, Hipp, Petersilia and Turner 2010, Kubrin and Stewart 2006), given the barriers to employment for formerly incarcerated people (e.g. Pager 2007), we focus on joblessness. To test our ideas, we use data from people on parole in Texas released between 2006 and 2010. Before turning to the data, we discuss the network of neighborhoods and the consequences for joblessness for people on parole. Given prior work showing racial/ethnic differences in job attainment (e.g., see Pager 2007, Western and Sirois 2018 as two examples), we also discuss how the consequences of the network of neighborhoods and spatial scale may differ across racial and ethnic groups.

The Network of Neighborhoods and Joblessness for People on Parole

Prior research considers several different ways to think about connections between neighborhoods from a network perspective, including gang networks (Papachristos, Hureau and Braga 2013, Tita and Radil 2011), co-offending networks (Papachristos and Bastomski 2018, Schaefer 2012), long term residential mobility (Sampson 2012, Sharkey and Sampson 2010), social network ties (Hipp, Faris and Boessen 2012, Hipp et al. 2013), overlapping routine activities (Browning, Soller and Jackson 2015; Browning et al. 2017; see also Wang et al. 2019), Twitter networks (Nolan et al. 2020), and leadership contacts (Sampson 2012). Given our interest in the joblessness of people while on parole, we focus on the structure of observed employment patterns between neighborhoods as captured by commuting flows between neighborhoods (see also work by Boessen 2014, Graif et al. 2017, 2019). In this case, a tie exists between two neighborhoods when residents commute to another neighborhood to work.

People on parole who live in a neighborhood with incoming commuting ties from more neighborhoods – higher *indegree*- are in a popular position within the network of neighborhoods. Note that this does not necessarily represent more incoming workers, but rather incoming workers coming *from more neighborhoods*. For example, one recent study showed that neighborhoods with higher indegree of Twitter networks tend to be unevenly spatially distributed and more clustered in downtown areas (Phillips et al. 2019). We argue that higher indegree may indicate a more competitive environment for finding a job. This competition may be particularly important as it has also been linked to recidivism (Chamberlain et al. 2016). As a result of more competition, more incoming ties from a broader diversity of neighborhoods puts people who live there in a structural disadvantage in the labor market. This implies that people on parole will have more joblessness when they live in neighborhoods with higher indegree. Somewhat similarly, it seems probable that the more commuting networks that terminate in a neighborhood, the more likely other people will look for jobs in this same neighborhood, suggesting more competition and therefore more joblessness for people on parole living in the neighborhood.

Hypothesis 1: People on parole who live in neighborhoods with higher indegree will experience more joblessness.

Whereas *indegree* focuses on how many neighborhoods send workers to a parolee's home neighborhood, as a second approach the *outdegree* of the neighborhood focuses on the number of different neighborhoods to which local residents commute for work. Neighborhoods with higher outdegree are expected to be more advantageous relative to other neighborhoods, and therefore be in a stronger economic position in the area. People on parole who live in neighborhoods with greater outdegree have more economic engagement and integration within the structure of the network of neighborhoods. These communities with stronger engagement and outreach may have more institutional resources (e.g., see Kelling et al. 2020), as well as access to opportunities through transportation channels. When people on parole live in a more advantageous structural position within the network of neighborhoods, they may also have more access to resources and information about the labor market (e.g., see Bellair 1997, Hunter 1985). Thus, people on parole who live in neighborhoods with higher outdegree are posited to be more interwoven into the economic fabric of the city, and thus have more opportunities for finding employment.

Hypothesis 2: People on parole who live in neighborhoods with higher outdegree will experience less joblessness.

Spatial Scale and the Network of Neighborhoods

Whereas the neighborhood's structural position in the larger commuting (economic) network may be important, the spatial distribution of those neighborhood network ties might have important consequences as well. Prior literature on neighborhoods, as well as the network of neighborhoods specifically, has most often not made a distinction between mico- or macro-scales, instead assuming all scales are relevant in the same way (or as a smooth distance decay pattern) or only focused on the micro nearby area (e.g., see Morenoff 2003, Peterson and Krivo 2010, Sampson 2012). However, recent emphasis on considering the activity patterns of individual people outside of the local neighborhood (e.g., see Browning et al. 2019) points to the need to examine broader spatial scales. Although we agree that the micro scale is likely important, we also argue that there is a need to simultaneously consider even broader meso and macro spatial scales. In this paper, we make a distinction between the different linkages a neighborhood has in the local micro area, the meso area, and at the broader macro scale. We define the micro scale to operate within 1 mile of a neighborhood, the meso scale to operate from 1-10 miles of the neighborhood, and the macro scale to operate more than 10 miles from a neighborhood.

These three spatial scales (micro, meso, and macro) may have different implications for our outdegree measures and their role in joblessness for people on parole. When considering indegree, we argue that the spatial scale of neighborhoods from where outside workers are coming would not matter for joblessness. To the extent that a person on parole resides in a neighborhood that is in a more popular position within the economic structure of the area, they may face more extensive external competition from other workers for the same position, and be in a more structurally disadvantaged position within the network of neighborhoods. The negative consequences for a neighborhood with more indegree would occur regardless of where those workers are coming from.

In contrast, the outdegree of the neighborhood may have differing consequences for joblessness depending on the spatial scale of the outgoing links. More outgoing ties to the local micro neighborhood (i.e., within 1 mile) may indicate that a person on parole will have an easier time gaining employment, because they are likely more knowledgeable about this area and a local job search is easier (e.g., it is walkable). Given the racial and economic segregation that exists in many cities (Krivo et al. 2013), the demographics of the people in the micro- and meso-scale neighborhoods may appear relatively similar (i.e., less social distance) to people on parole, and may make it easier to find employment. Additionally, areas at the meso scale likely have similar positive benefits as the micro scale but also provide other structural support through neighborhood contacts for finding employment (Hellerstein, Kutzbach and Neumark 2014) or support from local organizations and unions (Hunter 1985). A person on parole in a neighborhood with a more expansive set of meso scale economic links to other neighborhoods may be in a structural position providing more opportunities (e.g., more knowledge of jobs), and thus yielding better job prospects. Thus, we posit:

Hypothesis 3: People on parole in neighborhoods with more outdegree with the micro or meso area will experience less joblessness.

When considering the macro scale of outdegree, the costs and challenges associated with longer commutes and awareness of opportunities would likely mean that ties to more distant locations will not yield benefits for people on parole. This draws in part from a line of research stemming from the spatial mismatch between where people live and where jobs are available (Gobillon, Selod and Zenou 2007, Holzer et a. 1994, Ihlanfeldt 1993, Kain 1968, Mouw 2000, Raphael 1998a, 1998b; Stoll 1998, Stoll1999, Stoll and Raphael 2000). To the extent that many workers in a neighborhood are traveling long distances to jobs, their neighborhood is spatially disconnected from the broader city and region. Long commutes to work may be particularly difficult for people on parole because of significant barriers, including transportation access and lack of time (Bohmert 2016). Therefore, higher outdegree at the macro scale may result in more joblessness for parolees in these neighborhoods. This suggests:

Hypothesis 4: People on parole in neighborhoods with more macro-level outdegree will experience more joblessness.

The Network of Neighborhoods and Racial/Ethnic Differences in Joblessness

Beyond studies demonstrating that criminal records represent significant barriers to people on parole obtaining employment (Pager, 2007), a plethora of studies have shown that Black and Latino people in general have more difficulty finding a job than white individuals. Research suggest that this is in part because of differences in their job searches (Decker et al. 2014, Pager 2007, Pager and Pedulla 2015, Pettit and Lyons 2007, Stoll and Raphael 2000, Quillian et al. 2020), in access to and use of informal networks for getting jobs (Holzer 1987), in labor market networks (Hellerstein, Kutzbach and Neumark 2014), and spatial mismatch (Gobillon, Selod and Zenou 2007, Holzer et a. 1994, Ihlanfeldt 1993, Kain 1968, Mouw 2000, Raphael 1998a, 1998b; Stoll 1998, Stoll1999, Stoll and Raphael 2000).[1] We build on work by Sabol (2007), who found that Black people on parole have significantly longer time to first employment than other people on parole after being released from prison, using the county unemployment rate. We extend this study by considering multiple spatial scales and how neighborhoods are integrated with other neighborhoods in the network of neighborhoods.

Racial and ethnic differences of people on parole in tandem with the spatial distribution of people by race/ethnicity may have implications for joblessness. At the micro level, outdegree might not matter differently across racial and ethnic groups. Employers may have a homophily preference to hire those with minimal social distance to their local residents (see McPherson, Smith-Lovin, and Cook 2001 for a review on homophily). We expect that homophily is more likely to occur at smaller micro and meso spatial scales because of the racial segregation in many cities, making closeby neighborhoods more demographically similar. In this way, homophily may create benefits for local residents because employers may want to hire someone similar to them and their local customers. One implication of this pattern is that homophily will allow for more information on hiring and jobs at the micro and meso scale in a similar way for each racial/ethnic group, and accordingly more outdegree at these same spatial scales. As such, at the micro and meso neighborhood scales, more outdegree will be associated with better job prospects regardless of the race/ethnicity of the person on parole.

When considering macro spatial scales, the spatial mismatch thesis would predict that Black and Latino individuals have greater barriers in accessing jobs relative to white people

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[1] Although we use Latino in this study, we recognize that Hispanic ethnicity or gender neutral terms (Latinx) may also be appropriate, and there does not appear to be a strong consensus on which term is preferable: https://www.pewresearch.org/fact-tank/2013/10/28/in-texas-its-hispanic-por-favor/

(Gobillon, Selod and Zenou 2007, Holzer et a. 1994, Ihlanfeldt 1993, Kain 1968, Mouw 2000, Raphael 1998a, 1998b; Stoll 1998, Stoll1999, Stoll and Raphael 2000). This is in part because the distance to jobs is racially unequal due to segregation patterns, where white individuals have easier access to jobs relative to Black and Latino people.[2] Black and Latino people on parole may need to seek out employment in a broader variety of neighborhoods (i.e., higher outdegree), while white people on parole can benefit by finding jobs closer to them. Black and Latino people on parole may not necessarily be structurally isolated because they are spatially disconnected from other neighborhoods (as suggested by hypothesis 4), but because they are tied to so many other neighborhoods (see also Krivo et al. 2013). White people on parole may be structurally advantaged by living in *more* socially and spatially isolated neighborhoods in the network of neighborhoods.[3] Stoll and Raphael (2000) provides some evidence of this pattern by showing that Black people search more areas when looking for jobs than white people (see also Stoll 1999), implying that there might be a lack of opportunity at the micro or meso scale. If spatial mismatch is correct, we would expect that for Black and Latino people on parole higher macro scale outdegree combined with lower micro and meso scale outdegree will have negative consequences, implying:

> *Hypothesis 5: Black and Latino people on parole in neighborhoods with more macro-level outdegree will experience more joblessness when fewer micro or meso scale ties are present.*

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[2] A contrasting view is Massoglia et al. (2012), who found that white parolees have ‘more to lose’ following incarceration when compared to other groups, and thus white parolees may actually have worse job prospects.

[3] At smaller spatial scales, this isolation might be advantageous for different race/ethnicities to the extent that an ethnic enclave is present for structural support (e.g., see Wilson and Portes 1980).

Current Study Overview

In this study, we move beyond approaches that focus only on within neighborhood processes for job attainment for parolees, and capture a neighborhood's structural position and embeddedness in the network of neighborhoods based on observed employment patterns via commuting ties to work. We test our hypotheses for whether different features of the network of neighborhoods – indegree and outdegree – have consequences for joblessness for people on parole. We also test whether the outdegree of the neighborhood has differing consequences depending on the spatial scale of these networks, and whether these consequences are different across racial and ethnic groups.

Data and Methods

The main data source for our project comes from all people released on parole in Texas from 2006 to 2010.[4] Data were obtained directly from the Texas Department of Criminal Justice (TDCJ), and they included dates and locations of home addresses, dates of joblessness, employment information, and key demographic characteristics reported to parole officers. People were followed from their release date until the end of their parole (revoked, discharged, or death) or until July 2012. Our focus is on joblessness while on parole, and thus we only focus on people on parole who reported joblessness information and were on parole for at least one day. Our unit of analysis is a person- release spell- address spell. As such, people could be released multiple times and have multiple addresses (i.e., they moved). Each spell ends when the person on parole exits parole (i.e., discharged or death), has their parole revoked (i.e., re-arrested), or moves to a new address. Address residential spells do not necessarily end when people on parole have

[4] Our data are of all people released from Texas Department of Criminal Justice custody during the fiscal year. We only focus on people released from prison, and we do not include information on those who were discharged directly from prison or from a substance abuse facility. When we say 'released', this indicates that someone was released during these years, and this is not the total count of everyone on parole during this time period.

technical violations and are sanctioned to intermediate sanction facilities (Council of State Governments Justice Center 2009).

We initially obtained data from the TDCJ on 401,418 releases on parole from 2000-2011 (approximately 33,000 each year).[5] We focus only on parole or mandatory parole releases, bringing the sample to 390,650. We excluded all other types of releases, including those with missing release type information (1643), out of state releases (9107), or other rare release types with less than a few people (18 total releases). We next excluded 4.27% of the sample who were not released from the TDCJ prison (10,530 who were parole in absentia (i.e., those released from county jails, out of state facilities, or federal penal institutions), 3160 in state jails, and 2985 who were missing release institution information). As such, we only focus on those released from prison, and this brings the sample to 373,965. We further excluded people who were currently in custody (1129), and this brings the sample to 372,836. We also excluded people without any conviction information (425), and this brought the sample to 372,411. We further excluded another 1.44% (5387) who were missing demographic information, and thus the sample is now 367,024. We only focus on 4 main parole statuses (normal reporting, revoked, discharge or death) that represent 91.54% of the data, and this brings the sample to 335,983. We further excluded 107 releases that had missing release date information and 40 releases who had zero days on parole, bringing the sample to 335,836. We focus our analyses on those released between 2006-2010 because these data directly overlap with the years of our key independent variables, and we are only interested in cross-sectional models for our research questions.[6] This reduced the sample to 142,505 releases (136,073 individual people). We further excluded

[5] When we compared our sample sizes by year to the TDCJ reports, they were relatively similar (e.g. see page 34: https://www.tdcj.texas.gov/documents/Statistical_Report_FY2010.pdf). Note also given that we have multiple years of data, a person can be released multiple times (i.e., multiple spells).
[6] Prior to September 2004, the data also do not allow for capturing people who were released multiple times.

releases who did not have zipcode information (2040), lived outside of Texas (2011), or had other data issues (11), bringing the sample to 138,443 releases.

We next connected these data with a separate dataset that had address information for residences, and following that, another dataset with employment information. Of the 138,443 releases, 100,651 (72.70%) releases could be assigned to at least one specific address using their overlapping dates (225,066 person-release-address spells), and we excluded the other releases who had data issues (i.e., missing dates, did not spend at least a day at an address).[7] [8] We next connected these data with an additional TDCJ dataset that contained dates and whether someone was unemployed, employed, retired, a student, or disabled. Of the 100,651 releases, 3,177 were excluded because of data issues (e.g., errors in dates, zero days at a job), and this brought the sample to 97,353 releases. We only focus on releases that had employment or unemployment data (92.9%), and this excludes 6904 releases. [9] Thus, our main analytic sample is 90,449 releases (191,983 person-release-address spells).[10] [11] Of those, 72,170 releases (79.79%)

[7] The TDCJ staff provided only non-institutional addresses. Prisons, jails, treatment facilities and other institutions are not listed as addresses. We geocoded home addresses for people on parole using a combination of *Google* and ArcGIS's 2010 StreetMap data to the address level and joined them to a 2010 census tract. 87% of all releases with address information were able to be geocoded. The demographics between those geocoded and not geocoded were similar, giving us confidence in the data.

[8] We compared the demographics between those with and without residential information, and they were similar.

[9] We also tested models that included disability with unemployment. Indegree was still significant in these models, but not outdegree. Outdegree at the meso level was still significantly associated with reductions in unemployment and disability for Latino people on parole, but not for white or Black people on parole. As such, combining disability and unemployment suggests mixed patterns, implying that disability and unemployment may not always operate in the same way, and arguably should not be combined together. Further, we only focus on those with employment or unemployment information because 1.) it is arguably cleaner to only focus on those who reported being unemployed or employed in the administrative data (we did code those with full employment as zero days unemployed and tested models within and without this distinction and the results were similar), 2.) just because someone was not employed, it's not clear they are unemployed because they could be a student, retired, or disabled (and it is not necessarily clear they are looking for work or out of work for that matter), and 3.) it also seems plausible that someone reported being 'employed' to their parole officer, but they haven't started work yet (i.e., they got a job but did not start yet). We compared the demographics amongst employed vs. unemployed spells, and they are relatively similar, except white releases were more likely to have an employment spell, while black releases were more likely to have an unemployment spell, which is not surprising given the literature on parole. Accordingly, we examine differences by race/ethnicity in our models.

[10] 89.86% of those with address information had employment or unemployment data.

experienced unemployment for at least a day.

On average, people on parole in our data spent 265 days at an address with employment or unemployment information (the median is 167 days, or about 5.3 months. See also Herbert et al. 2015). We use 2010 Census tracts to represent neighborhoods, given that they provide proxies for neighborhoods and a broad enough spatial scale to capture the economic structure between different neighborhoods. The total number of unique census tracts is 5,134 with an average of 37.4 spells per tract (median = 27, interquartile range = 38, mean people on parole per tract = 30.6).[12]

We also use data from two additional sources. First, to capture the neighborhood characteristics, we use the American Community Survey 5-year estimates (2006-2010). Second, we use data on employment patterns with the 2006-2010 Census Transportation and Planning Products (CTPP) that contains information on job locations and commuting.[13] These data are based on large sample surveys conducted by the Census Bureau, and the 2006-2010 data is a special tabulation of the American Community Survey. All employers and industry categories are included in the sample universe. The data only contains information on primary workplace and does not include information on second jobs or people working under the age of 16. It does include self-employed people. We assume the data are missing completely at random (MCAR).

Dependent Variable

Our key outcome variable is the number of days that a person on parole reported being jobless. In Texas, people on parole verify their employment status and dates of this status to their

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[11] The difference of 54 releases between the analytical sample and the samples in the tables are due to missing data on the covariates (e.g., neighborhood data).
[12] There are a total of 5265 census tracts in the 2010 census in Texas, and thus there are 131 tracts that did not have any people released on parole for our data (2.4% of the tracts in all of Texas).
[13] More information on these data is located here: https://ctpp.transportation.org/

parole officer each month, and parole officers are required to file this information into an electronic system within 3 days. We focus on the days a person on parole is jobless given this is the most crucial time period that reoffending is likely to occur. We account for the length of time (in days) that someone is at the address with any unemployment or employment information as an exposure term in our analyses.

Independent Variables

Network of Neighborhoods

Our network measures capture the structural position of a neighborhood relative to other neighborhoods in the region. To assess the network of neighborhoods we compute two common centrality measures: indegree and outdegree. We capture links between neighborhoods using the commuting data from the CTPP, and therefore two neighborhoods are tied if a neighborhood sends people to work in another neighborhood (i.e., home -> work). Thus, these commuting networks are essentially an edgelist, where any tract can be tied to any other tract in the United States. We only focus on ties in Texas and all nearby states (Arkansas, Colorado, Kansas, Louisiana, New Mexico, and Oklahoma) in the computation of our degree measures. To be included as a tie, the census requires a minimum of 4 workers to be sent between tracts.[14] Because studies suggest that parolees tend to be employed in lower-income jobs (Crutchfield 2014; Sugie and Lens 2017), we only focus on low income job commuting networks (jobs making less than $25,000 a year).[15]

We capture the competition (i.e., popularity) of the neighborhood with a measure of

[14] We do not include ties where the sending and receiving nodes are the same in our degree computations (i.e., living and working in the same neighborhood). When constructing measures including same neighborhood ties, they were essentially identical to the measures without these reflexive ties.

[15] We also tested models that included different thresholds for low income (e.g., $35,000). The results were substantively similar giving us further confidence in our results.

indegree, which is computed as the number of neighborhoods that send workers to a parolee's home tract. We also capture *outdegree*, which is computed as the number of neighborhoods to which residents in a parolee's neighborhood travel for work. Indegree and outdegree are only correlated at .10, suggesting many asymmetries in these economic links, and the fact that these measures are tapping different aspects of the neighborhood network structure. We also consider whether there are differences in the spatial scale of the network of neighborhoods. Using the distance between tract centroids, we capture outdegree at three spatial scales: the micro neighborhood (within 1 mile [1.6 km]), the meso area within 1-10 miles [1.6km -16.0km], and the macro scale that is greater than 10 miles [greater than 16 km].[16] [17]

Neighborhood Unemployment Context

Whereas the neighborhood network measures focus on a structural position relative to other neighborhoods, we also include more common measures of the employment context: the unemployment rate in the neighborhood and the job environment nearby. First, we suspect that the unemployment context of the local neighborhood will affect a parolee's joblessness. We therefore compute the percent unemployed in the neighborhood using data from the American Community Survey. Second, given prior research suggesting that many neighborhood

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[16] There is no clear agreed upon distance for how to best capture these differing spatial scales, and we choose the 1 mile distance due to the walkability of neighborhoods (1 mile is approximately a 20 minute walk, see Talen and Koschinsky, 2013) and 1 mile is also the basis for neighborhood perceptions from the General Social Survey. The 10 mile range is often used to represent the broader neighborhood area (e.g., see Boessen and Hipp, 2015), and we also note that the median distance between home and work zipcodes for people on parole released in Texas is approximately 8 miles, suggesting the 10-mile cut off as being not entirely arbitrary. We also computed a 5 mile cutoff rather than 10 miles, as well as 5 mile spatial lags of neighborhood controls. The two outdegree meso scale measures at 5 and 10 miles are correlated at .85 and the two macro scale measures at .84. There were no substantive differences in the model results. One slight change is that for Latino people on parole, the macro scale rather than meso scale outdegree was associated with reductions in unemployment. Neighborhoods with higher indegree for white people on parole also had significantly more unemployment, suggesting a competition effect similar to Black and Latino people on parole.

[17] Although we only focus on outdegree at various spatial scales, we note that the correlation between meso and macro outdegree is .08, while the correlation between meso and macro indegree is .78, suggesting differences of outdegree over broader spatial scales.

characteristics are not confined to a neighborhood but also the nearby area, we include a spatial lag of the unemployment rate and a spatial lag of the number of jobs nearby (logged), based on CTPP data.[18] We computed these lags as a 10-mile [16 km] inverse distance decay. We included all tracts within 10 miles—even those outside of Texas—given that omitting these edge effects otherwise biases the results (Wong 1997).

Measures of Neighborhoods and People on Parole

We include several control variables that capture neighborhood and people on parole characteristics. First, we capture the racial composition of the neighborhood, with measures of the percentage Black residents and the percentage Latino residents. We also assess the extent of racial mixing in the neighborhood with a measure of racial/ethnic heterogeneity as a Herfindahl index of five racial/ethnic groupings (White, Black, Latino, Asian, other races). Given heterogeneity's adverse role in the formation of social ties (Bursik and Grasmick 1993), people in neighborhoods with more heterogeneity might experience more joblessness. More residential turnover may affect the ability to gain employment for people on parole, and we capture the residential instability of the neighborhood with a factor analysis of the average length of residence in the neighborhood and the percentage of households who are homeowners. Given prior work suggesting distinctions between people on parole in various urban and rural environments (Eason 2017, Simes 2018), as well as work on micro and macro population patterns (Hipp and Roussell 2013), and the geography of Texas, we include a measure of the logged population within 20 miles of a parolee's census tract. We also include a measure of tract population density (number of people per square mile) to capture population differences in the local area. Given that economic disadvantage is a key determinant of job attainment (Morenoff

[18] The correlation between the spatial lag of percent unemployed and the logged number of jobs within 10 miles is .2, suggesting that they are related but capturing different features of the local employment context.

and Harding 2011), we include the percent of residents in poverty. Finally, for all measures, we computed spatial lags of the surrounding area, and these spatial lag measures were computed with a 10 mile [16 km] inverse distance decay (for a similar approach see Morenoff 2003).[19]

Because we are interested in testing our models by race/ethnicity, we also examine whether the person on parole was reported as Black, or reported as Latino, to the Texas Department of Criminal Justice. Our models also include several control variables for the characteristics of people on parole. First, we include demographic measures for sex, age in years, or whether someone reported being married.[20] Second, prior criminal history likely affects joblessness, and we include a measure of whether a person on parole was convicted of a violent crime. Third, we control for type of release with an indicator for whether a person on parole's release type was simply parole or mandatory released.[21] Mandatory release occurs when someone is released from prison due to serving the length of their sentence (based on calendar time and good conduct time). We suspect that those who are mandatory released are less prepared for parole and thus they will likely have longer stints being jobless. Finally, we control for sentence length in years that a person on parole was sentenced to prison.[22]

Methodological Approach

Our key outcome measure is the number of days a person on parole was jobless at an address. Each spell on parole and address is represented as a new row in the dataset. Given our outcome measure is a count and the structure of the data, we estimated multilevel negative

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[19] Given the size of some tracts in Texas, a 10 mile lag based on distance and centroids does not always include nearby tracts. When this occurred (N=487), we computed our distance decays based on the five nearest tracts.
[20] Our data only has information on whether someone is currently married at the most recent release.
[21] We cannot determine from the data whether someone is mandatory release or discretionary mandatory released.
[22] Only the most recent sentence length is available. One study of short-term confinement in the Netherlands found that longer sentences were associated with less employment (Ramakers et al. 2014). For those in prison, a longer sentence length could result in more stigma and loss of job skills, resulting in longer jobless spells. An alternative possibility is that a longer sentence length could provide people on parole more motivation to find employment, which might reduce joblessness (Kling 2006).

binomial regression models with parolee release spells nested within tracts using the menbreg command in Stata. [23] We also adjust our standard errors for the clustering in counties. We include the number of days at an address with employment information as an exposure term and thus our outcome is effectively a rate that adjusts for the varying exposure of time on parole at different addresses. [24] Although this measure is technically range-restricted, given that the number of days is capped at the number of days at a location, in practice this measure exhibits an overdispersed Poisson distribution. The individual-level equation can be expressed as:

$$\log(E(y_{ik} \mid X_{ik}) = \eta_k + \Gamma X_{ik} + \log(\text{expos})_{ik} + \nu_{ik} \tag{1}$$

where y_{ik} is the number of jobless days for the *i*-th respondent of *I* respondents in the *k*-th neighborhood, η_k is random effect for the neighborhood, X_{ik} is a matrix of exogenous predictors with values for each individual *i* in neighborhood *k*, Γ shows the effect of these predictors, $\log(\text{expos})_{ik}$ is the logged exposure time, and ν_{ik} has a gamma distribution that captures the overdispersion.

The neighborhood-level measures are included in the second equation:

$$\eta_k = B_N Z_k + \varepsilon_k \tag{2}$$

where η_k represents a random intercept of the overall average number of jobless days in neighborhood *k*, Z_k represents a vector of variables measured at the level of neighborhood *k*, B_N

[23] Given that people on parole have differing numbers of spells, we estimated models that included the number of spells as a series of dummy variables (minus 1), and these results were similar to those shown in the tables. As another approach, we also estimated three-level multilevel models, and they encountered estimation difficulties, although the estimates produced were relatively similar to those shown in the tables. Finally, we also tested models that compared only the first spell of parolees, and the results were substantively similar (for a similar approach for this issue see Hipp, Petersilia, and Turner, 2010).

[24] A question arises as to whether those who spend fewer days on parole are distinct from those who spend more days on parole. While we control for days at an address with employment information as our exposure term, this does not adjust for length of parole overall. To assess this possibility, we estimated ancillary models that included a measure of days on parole, and the inclusion of this measure did not alter our substantive findings. We also tested models that only included people who spent less than 100 days at an address with employment information (about 34% of the data), and the results were similar to those shown in the text.

shows the effect of these measures on number of jobless days, and ε_k is a disturbance for neighborhood *k*. We did not have any issues with collinearity or outliers.[25] The correlation between logged number of jobs within 10 miles and the spatial lag of population density is highly correlated (.82). While this is not surprising, this also is not problematic for our models given the large sample size: given our sample size of neighborhoods, a VIF value of 21 or less would provide us equal or better information as a simple regression model with a sample of 200 and an R-square of .20 based on the equations of O'Brien 2007.

Our analyses begin by first assessing our key indegree and outdegree centrality measures and their consequences for joblessness. We then turn to assessing whether there are spatial differences in our degree measures. Finally, we assess any racial/ethnic differences in our findings. We also estimate several supplemental models to strengthen our results.

Results

Before turning to the models, we briefly discuss the key summary statistics shown in Table 1. On average, people on parole spend 80.93 days jobless at an address. The summary statistics show that Black people on parole experience over a month longer of joblessness compared to white or Latino people on parole, on average. When looking at the network measures, Black and Latino people on parole have *more* ties to other neighborhoods compared to white people on parole. Specifically, Black and Latino people on parole live in neighborhoods that have greater indegree and outdegree than those of white people on parole. When looking at outdegree, most ties appear to occur at the meso level within 1 to 10 miles. Although there is relative similarity amongst the different racial/ethnic groups for neighborhood macro outdegree,

[25] Collinearity was tested with Philip Ender's Stata ado file: 'collin'. All variance inflation factors were under 10. We tested for outliers using studentized residuals from models estimated as linear regressions (the outcome was converted to a rate). We then estimated models without observations with studentized residuals greater than or less than 2, and the results were the same.

Black and Latino parolee neighborhoods have considerably more meso outdegree than those of white parolees. Black and Latino parolee neighborhoods also have slightly more indegree. When considering the network of neighborhoods of low income commuting networks, parolees' neighborhoods are tied to a broad array of other neighborhoods in both incoming and outgoing ties, and Black and Latino parolees have more indegree and meso outdegree associated with their neighborhoods.

A question arises about how a tract for a typical person on parole compares with the average tract for Texas. When looking at indegree and outdegree ties based on low-income jobs, the average Texas tract has 8.45 indegree and 8.46 outdegree, and thus when compared with the means in Table 1 (10.06 for indegree and 11.19 for outdegree), people on parole have higher indegree and higher outdegree. When looking at the low-income indegree and outdegree for a typical majority Black, Latino, or white tract in Texas (greater than 70% for a particular group), majority Black tracts have indegree = 6.4 and outdegree = 11.2, Latino tracts have indegree=10.9 and outdegree=13.2, and white tracts have indegree = 6.0 and outdegree 4.9. As such, majority white tracts are less connected in the low income network of neighborhoods. When comparing these majority tracts with neighborhoods of people on parole in Table 1, we see that neighborhoods of people on parole have more indegree (competition) than majority Black or white neighborhoods (majority Latino neighborhoods are similar), suggesting Black and white people on parole face more structural competition. While Black and Latino majority neighborhoods are similar in terms of outdegree, majority white neighborhoods have approximately half the number of structural supports (outdegree) in the low income network of neighborhoods when compared to neighborhoods of people on parole or even white people on parole's neighborhoods. Overall, Black and Latino neighborhoods are structurally tied to more neighborhoods on average, and white neighborhoods appear spatially isolated in the low-income network of neighborhoods.[26]

<<<Table 1 about here>>>

Turning to our models, we begin by discussing model 1 in Table 2, where joblessness is explained by classic measures of the local labor market context: unemployment, the spatial lag of unemployment, and the job environment within 10 miles of the neighborhood. Unsurprisingly, the neighborhood unemployment rate is significantly associated with more joblessness for people on parole, and we also see that more unemployment in the nearby area surrounding the neighborhood (i.e., the spatial lag) is also associated with more joblessness. A person on parole who lives in a high unemployment neighborhood (one standard deviation higher) is associated with 1.4% more jobless days (exp(.003*4.86)-1=.014), and the spatial lag of unemployment is associated with 6.4% more jobless days (exp(.0313*2.01)-1=.064), suggesting that the broader area impacts a parolee's joblessness.[27] The presence of more jobs within 10 miles is also associated with less joblessness. Taken as whole, the presence of more people working and more nearby jobs are suggestive of better job prospects for people on parole.

Turning to the structural position measures in model 2, higher indegree is associated with more joblessness as hypothesized (hypothesis #1). When people on parole live in a neighborhood

[26] When looking at the indegree and outdegree for all kinds of ties (i.e., based on jobs of *all* incomes) for a typical majority Black, Latino, or white tract in Texas, the values are for majority Black tracts (indegree = 48.1, outdegree = 46.2), for majority Latino tracts (indegree = 54.0, outdegree = 49.2) and White tracts (indegree = 45.0, outdegree 55.9). Black and Latino neighborhoods have more competition, but when looking at outdegree for all jobs, majority white tracts have more structural support. We also emphasize that over half of the tracts in Texas are not majority white, Black, or Latino.

[27] Some people on parole were released during the Great Recession. With a plethora of skilled workers laid off during the recession, we expect parolees to fair even worse in a labor market with many unemployed workers. To test this idea, we used a dummy variable to indicate whether someone was released prior to 2008 and those released from 2008 on. The dummy variable was significant, suggesting those released during the recession had more days unemployed, but the other results were substantively similar. When we interacted this dummy variable with our key measures, it was significant when interacted with indegree. This effect showed that indegree was significantly stronger during the recession as might be expected given the recession context. We also tested models that included year of release as a series of N-1 dummy variables, and their inclusion did not substantively alter the main results.

with one standard deviation higher indegree, they are expected to have 2.0% more jobless days. This pattern suggests that people on parole who live in more popular neighborhoods may face a more competitive labor market, resulting in longer spells of being without a job.[28] On the other hand, when considering outdegree, people on parole who live in neighborhoods with one standard deviation more outgoing job commuting ties to other neighborhoods have 2.8% fewer jobless days.[29] Thus, we find support for our second hypothesis. We also see that these measures, and the other associations noted, are robust when we include our spatial lag measures of the surrounding neighborhood characteristics in model 3.

Models 4-7 in Table 2 assess our outdegree measure at differing spatial scales. First, while there is no evidence of a micro outdegree effect within 1 mile of a person on parole's home or a macro effect beyond 10 miles, people on parole who live in neighborhoods with one standard deviation more job ties being sent to the meso area (within 1 to 10 miles) tend to experience 4.6% *fewer* days jobless. Therefore, our third hypothesis specifying that people on parole in neighborhoods with higher outdegree from the micro or meso area would experience less joblessness is supported for meso areas, but not micro areas. Similarly, our fourth hypothesis that neighborhoods with more macro outdegrees will experience less joblessness was not supported. This pattern does show that the consequences of outdegree differ depending on the

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[28] Note that this effect is controlling for the unemployment rate in the neighborhood. We estimated ancillary models without the unemployment rate in the neighborhood or nearby area and the results were nearly identical, further indicating that our structural network measures are distinct from neighborhood unemployment. We also tested interactions between unemployment and our degree measures, and none were significant. Finally, we also estimated models with neighborhood unemployment as the outcome and our indegree and outdegree measures as predictors along with our other neighborhood measures. While indegree was not a significant predictor, we did find that outdegree was associated with less unemployment, suggesting some of the effect of unemployment is through structural outdegree (i.e., lack of external support). This also indicates that the effect of indegree is distinct from unemployment.

[29] One possibility is that high values of outdegree may indicate more joblessness due to the broader diversity of economic links, and low values of outdegree indicate an isolation effect and thus also more joblessness (a convex 'U-shaped' association). We tested these ideas with models that included a nonlinear effect for both indegree and outdegree (a squared term). We found no evidence of this pattern for indegree or outdegree.

spatial scale of the ties, but there is no evidence that a micro or macro focus exclusively would capture these structural patterns. When people on parole live in neighborhoods with more outdegree at the meso scale, they have better job prospects, suggesting that this spatial scale is important for structural support.

<<<Table 2 about here>>>

When looking at the neighborhood characteristics, poverty is consistently associated with more days jobless. A one standard deviation increase in poverty is associated with 4.7% more days jobless. We see little evidence that residential stability in the neighborhood affects days jobless, but we do see some evidence that residential stability in the nearby area is associated with fewer days jobless, suggesting that this stability may translate into more support in finding a job from local networks.[30] We also see that when people on parole live nearby ethnically heterogeneous areas, they have fewer days unemployed. This might indicate that being in a diverse neighborhood allows access to new information and resources not present in homogeneous areas. People on parole living in neighborhoods with more population density or more population within 20 miles (i.e., the macro environment), experience more joblessness, implying a beneficial effect in less dense areas. As we note later in our supplemental analyses, we also test interactions between these population measures and our degree measures.

Finally, the parameters for the demographic and individual characteristics of people on parole in all models appear relatively consistent. Males on parole are significantly less likely to be jobless implying that access to the labor market differs by gender for parolees, and this is somewhat expected given longstanding gender gaps in employment. There is also a small

[30] Although not of primary interest for this project, a concern is residential mobility of people on parole. For our study, if someone moved (even within the same neighborhood), it is a new spell. To assess this issue, we estimated models that only focused on the first address reported by someone on parole. The results were largely similar to those in the tables, which gives us further confidence in the results.

nonlinear effect for age in which older people on parole are more likely to be jobless, which may indicate a mismatch of the skills of older parolees with work in the modern economy. Married people on parole are much less likely to be jobless, which is in line with the life course literature positing that marriage has positive life outcomes. People who are mandatory released into the community have more days jobless compared to people on parole. Sentence length was negatively associated with joblessness, suggesting that those with longer sentences experience less joblessness.[31] Finally, when looking at the patterns by race/ethnicity, Black parolees are significantly more likely to be jobless compared to white/other parolees, but Latinos were not significantly different when compared to white/other people on parole. To further unpack these findings, we estimate models by race/ethnicity of the person on parole.

Table 3 assesses whether there are differences by race/ethnicity of the person on parole by estimating separate models for each group (full results in Appendix A). [32] The descriptive pattern of the various degree measures shows that white people on parole had slightly fewer indegree ties from other neighborhoods than Black or Latino people on parole but considerably less meso outdegree. One key pattern in Table 3 is that indegree is significantly associated with more joblessness for black and Latino people, but not white people. When looking at the consequences of indegree for joblessness, a one standard deviation increase in indegree is associated with 3.2% more joblessness for Latino parolees, but only 1.6% for Black parolees, suggesting a slightly stronger association for Latino people on parole for this structural

[31] This result was unexpected, and future research with other datasets might examine different approaches to assessing this negative association. One possibility is that this effect has to do with the fact that our data is only of the most recent sentence length. Another possibility is that this negative effect is due to people with longer sentences being more motivated and supported while on parole (see also Kling 2006 for a similar finding). We also tested whether this effect was nonlinear, and while it was significant, when plotted, it appears relatively linear.

[32] To further assess these patterns, we also estimated some ancillary models that tested interactions between race and our degree measures. The results indicated that the effect of indegree did not significantly differ between white and Black people on parole and white and Latino people on parole. The results were otherwise substantively similar.

competition measure.

When looking at the models broken out by spatial scale, we see that meso outdegree is significantly associated with less jobless for all racial/ethnic groups, suggesting a structural support mechanism. A one standard deviation increase in meso scale outdegree is associated with 6.1% less jobless days for white parolees, 4.0% less jobless days for Black parolees, and 4.4% less days jobless for Latino parolees.[33] There is no evidence that micro scale outdegree has consequences for days jobless. There was some evidence that more macro scale outdegree for white parolees was associated with 2.5% more days jobless, suggesting that when white people live in more spatially distant connected areas, they have worse job prospects. Even still, the structural support for parolees associated with outdegree has some of the strongest associations in our models.

<<<Table 3 about here>>>

Taken as a whole, our models examine the independent effect of each of these spatial scales. However, the spatial mismatch literature and our fifth hypothesis implies considering how the micro or meso scale interact with the broader macro level context. To assess this possibility, we estimated models testing an interaction between our micro and macro outdegree measures, and an interaction between the meso and macro outdegree measures (results not shown in the

[33] An alternative strategy would be to adjust our spatial degree measures by the opportunity for forming ties. We assessed this by dividing the meso outdegree measure by the number of neighborhoods within 1 to 10 miles. When multiplying this by 100, it is the percent of neighborhoods that a neighborhood is tied to within this buffer. On average, a tract is tied to 16% of possible tracts within the 1 to 10 mile buffer. This adjusted outdegree measure was never significant when included in the models, but it was significant for black people when we logged this measure given the excessive skew (the coefficient was negative, and a one standard deviation increase in logged adjusted outdegree was associated with 3.9% fewer jobless days). Thus, this approach yielded results somewhat consistent with those in the paper. We also emphasize that a degree standardization strategy is not of substantive interest in this study given that we are comparing the role of a neighborhood within the broader constellation of the entire state and not necessarily those bounded to one particular metro or region. We also point readers to our supplemental models shown in Appendix B that test differences by size of population in the broader area.

Tables).[34] None of these interactions were significant when we estimated models with all racial/ethnic groups combined. When looking at differences by racial/ethnic group, none of these interactions were significant for Latino or white people on parole. For Black people, only the interaction between micro outdegree and macro outdegree was significant, but when plotted, this effect demonstrated little substantive difference. Overall, these results provide no support for spatial mismatch being a key driver of joblessness while on parole.

Sensitivity Tests: Urban and Rural Areas and Population Density

Most parole research focuses on urban areas, but recent work finds that rural areas (Eason 2017) and less dense urban areas (Simes 2018) may be important as well. When considering the geography of Texas, a question arises of whether our measures are robust to changes in population density. For example, urban areas may have much more competition (higher indegree) than more rural areas. Our earlier results also show that population density within the tract and the broader 20 mile area were both associated with more joblessness. This suggests a need to test interactions between population density, the population within 20 miles of a tract, and our measures of degree. The full models are shown in Appendix B.[35] [36] Even with our large sample size, no significant interactions occurred between our key measures and various density

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[34] We also estimated ancillary models including interactions of our various degree measures at the meso and macro spatial scales with the poverty and unemployment rates. None of the interactions were significant. We also tested these models by race/ethnicity of the person on parole and found no differences. Thus, these results are not consistent with a spatial mismatch explanation.

[35] When looking at the descriptive statistics, in urban areas, the average low income indegree is 10.5 and outdegree is 11.7, but in rural areas these values are just 2.6 and 3.0. Urban people on parole also spend 2 weeks longer jobless on average.

[36] We also tested models separately by race/ethnicity. While some of the interactions were significant, when we plotted them, we do not see any substantive difference, suggesting this is likely due to our large sample size. As such, these results are largely consistent with those in Appendix B.

measures.[37] Taken as a whole, these models indicate no differences over different population densities for people on parole in the consequences of the network of neighborhoods in their joblessness.

Sensitivity Tests: Commuting Flows, Tie Weight, and Jobs within 10 Miles

In this paper, we have focused on the structural economic connections between neighborhoods. Another approach is to consider the activity patterns of communities implied by routine activities and research on shared activity spaces. Whereas our indegree and outdegree measures capture the number of different neighborhoods that a neighborhood is tied to through commuting, commuting activity flows capture the number of people commuting in and out of the neighborhood. As such, it is interesting to determine whether our structural degree measures are distinct from commuting flow measures. To assess this possibility, we created several flow measures and tested additional models (see Appendix C). First, low income networks of neighborhood measures and activity flows of low income commuters are highly correlated: indegree is correlated with incoming commuters at .98, outdegree is correlated with outgoing commuters at .86. These correlations suggest little substantive difference between measures of degree and commuter activity flows. Neighborhoods with higher degree also tend to have more people who commute (i.e., higher activity level). The results of the models with commuters are also substantively quite similar (see models 1-2 in Appendix C). We also see no difference for commuting flows for people who commute within the same neighborhood (model 3). In model 4,

[37] To further examine the robustness of our results, we tested whether the patterns differ for rural or urban areas. We defined areas with more than 50,000 people within 20 miles as urban (everyone else was rural). We used a population cutoff of 50,000 within 20 miles because the United States Census defines this as the minimum city population size for the central city of a metropolitan area, and as the total maximum population for a micropolitan area. The inclusion of this dummy variable did not substantively change the findings (whether or not we included the logged population measure within 20 miles). We also tested a series of interactions between the urban/rural dummy variable and our network of neighborhoods measures, and none of these interactions were significant.

we include a measure of the number of people on parole in the neighborhood, and we see that when more people are on parole in the neighborhood, they are associated with more joblessness (a standard deviation increase in the number of people on parole is associated with 5.6% more days jobless). This result implies an additional (and considerable) competition effect above and beyond the role of incoming workers from other neighborhoods.

The final set of models in Appendix C assesses the job environment and our measures of degree. First, we tested a weighted outdegree measure that focuses on not simply to whom a neighborhood is tied but also the number of jobs in other neighborhoods (e.g., job hubs).[38] While this measure was initially not significant, when we logged this measure given its excessive skew, it was significant. A one standard deviation increase in weighted outdegree is associated with 6.6% more jobless days, suggesting that being tied to a job hub is not conducive to better job prospects for people on parole. Finally, we also tested interactions between our degree and commute flow measures with the number of jobs within 10 miles, and we do not have any evidence of significant differences for these interactions.

Discussion

Scholars have long examined the job prospects of people on parole. While most studies focus on individual characteristics of people on parole, our study shows that neighborhood economic networks based on commuting flows have consequences for job attainment. Our results provide evidence that a neighborhood's structural economic position based on commuting flows matters for joblessness. Importantly, commuting links to other neighborhoods are not

[38] To compute this measure, we again used the CTPP commuting edgelist data. We computed the outdegree of a neighborhood for all jobs, then multiplied this by the number of jobs in the neighborhoods in which all residents worked. We then logged this measure given the skew. This measure is correlated with our low income outdegree measure at .33.

necessarily always beneficial, but instead depend on whether the links are incoming or outgoing, and the spatial distribution of the links. Taken as a whole, the network of neighborhoods provides some insight into an additional structural aspect people on parole face when looking for jobs in the local labor market, including competition and support.

One key finding is that indegree and outdegree were shown to have *opposite* consequences for job attainment, with both findings supporting hypotheses 1 and 2. These measures were on par or even stronger for explaining parolee joblessness than some traditional key neighborhood measures (i.e., poverty and unemployment). Indegree is associated with more joblessness and indicative of external competition to the local area. More outdegree, particularly at the meso scale, has positive employment consequences, which is suggestive of a structural support mechanism. The findings support a need for future research to capture the structure of the network of neighborhoods, various positions within this structure, and how people are embedded within it. The competition finding indicates that more ties from a broader diversity of neighborhoods is not always beneficial, particularly for black and Latino people on parole. This structural competition effect has also been suggested by prior work on recidivism (Chamberlain et al. 2016), but our network measures allowed us to test this competition effect more directly. This pattern further indicates that there are structural barriers for people on parole when looking for jobs that are not directly linked to individual people on parole.

The spatial structure of the network of neighborhoods is also not an entirely local process, as our models indicated differences at various spatial scales (micro, meso, and macro). Whereas scholarship that examines the area surrounding the local neighborhood typically only focuses on what we defined as the micro neighborhood scale (within 1 mile), we saw no evidence of this micro scale having consequences for joblessness for people on parole. We did find that more outdegree neighborhood ties at the meso scale (within 1 to 10 miles) were associated with *less* joblessness. These results are consistent with the idea that more outgoing ties to nearby meso-scale neighborhoods may put these people on parole in a structurally advantageous position that provides job information, support, access (and exposure) to resources outside of the neighborhood, and more potential awareness of employment opportunities. Overall, these findings support hypothesis 3. In contrast to the beneficial effects we found for meso neighborhood ties, we found little evidence that macro outdegree impacted joblessness, and thus we do not have support for hypothesis 4. There was some modest evidence that when white people on parole live in neighborhoods with more macro outdegree, there are worse job prospects, and this pattern suggests challenges with obtaining employment (e.g., a lack of access to transportation) over broader spatial scales. Overall, we found little support for a macro scale, but we emphasize that a 10-mile meso scale will encapsulate nearly all regional urban areas in Texas (and likely most urban areas across the United States for that matter). As such, this pattern suggests a need to focus regionally rather than simply locally to understand parole patterns.

We found some evidence of different consequences for structural and spatial positions for different racial and ethnic groups. More meso outdegree appeared to reduce joblessness for all of the racial/ethnic groups, suggesting these ties to the broader meso region appear particularly important for reducing joblessness. But, there was some evidence that the benefits of these meso inter-neighborhood linkages were stronger for white people on parole, even though they had fewer meso ties on average. At the same time, only black and Latino people on parole were associated with more joblessness when located in areas with more incoming commuting ties, suggesting a stronger competition effect for black and Latino people. As such, this pattern suggests that white people on parole benefit by having not only stronger structural supports, but also weaker competition when looking for jobs than black or Latino people on parole.

Nonetheless, our data showed that black people on parole experience approximately a month longer jobless than other racial/ethnic groups on parole (see also work by Pager 2007), and thus it is still somewhat of an open question for these data as what is driving these disparities in joblessness. When considering black people on parole, we had little evidence of the network of neighborhoods having unique consequences for joblessness. There was also no evidence in support of spatial mismatch theory and hypothesis 5, as there were no employment differences found for Black parolees based on outdegree or for interactions of outdegree at various spatial scales. Other research in Texas has also shown that the issues in hiring are not about spatial mismatch. Black people often live in centralized downtown areas that have better access to jobs that are physically located in these same areas, and these researchers have noted that the issue is race, and not space per se (Cohn and Fossett 1996). Our results are consistent with this pattern in that the disparities appear to be driven by processes other than spatial mismatch for Black people (e.g., see Pager 2007, Quillian et al. 2020) and some of this is arguably due to differences in 'competition' for jobs that is likely a racialized process. Given that the spatial mismatch thesis is rooted in "Rust Belt" cities that have been economically hollowed out, our findings suggest that this thesis may not generalize to the Sunbelt, particularly Texas. As such, this reminds us that our theories are unlikely to be universally applicable over space.

Our sensitivity tests indicated that our measures of degree based on number of neighborhoods were highly correlated with measures that counted the number of people in these commuting flows. These two different measures also had similar consequences for joblessness. With the growing interest in more spatially and temporally precise data (i.e., GPS) to understand situational patterns, activity spaces of people, and ambient populations at different times of day, the similarity between our structural measures and commuting flow measures indicates that our structural measures may work quite well. The durable structure of ties between neighborhoods and spatial position of a neighborhood in space may serve as a reasonable proxy for and determinant of situational patterns, and may work as well as other approaches that situate people more precisely in continuous spacetime (see also Sampson and Levy 2020). This seems reasonable given that we would expect residential locations to be a strong determinant of activity patterns (see also Krivo et al. 2013) given the strong effects for distance and geographic space for social life (Butts et al. 2012). Of course, it depends on the research question, but our structural ties measures may also be considerably easier to measure, cheaper, and less prone to measurement error than other approaches that try to situate people at different times of day.

An important consideration for future research is exploring the mechanisms underlying our results. For instance, we have posited that these commute flows are providing information, support, and resources to people on parole, but future research would want to assess whether this is indeed the case. Another possibility is that commute flows change personal networks, and an interesting avenue for future research would be to assess whether personal networks of people on parole relate to the network of neighborhoods (see Boessen et al. 2017; 2018; Butts et al. 2012, Western and Sirois 2018). The personal contacts of people on parole may provide links connecting multiple neighborhoods and resources. For example, when people in general look for a job as well as people on parole, they will often turn to kin and friends (Visher, Debus-Sherrill and Yahner 2011, Visher, Debus and Yahner 2008), people inside their neighborhood (Vandecasteele and Fasang, 2020), as well as citywide institutions, unions, and organizations. Future research may want to test how these relationships, organizations, and their spatial distribution provide resources and connections between multiple neighborhoods. Relatedly, our strategy aggregated commute flows into measures of neighborhood in- or out-degree, future research may wish to model these neighborhood network ties through an exponential random graph model (ERGM) to further explore these patterns (e.g. see Graif et al. 2017).

We acknowledge some limitations to our study. First, we do not have measures of job skills or work experience. Although this is a common challenge of administrative data (National Research Council 2014), future research will want to test this possibility more explicitly. For example, future research might capture how job skills of people on parole interact with the kind of jobs present in their local labor market. Their experiences prior to prison may also be important, including prior employment experience (Harding et al. 2018, Massoglia et al. 2013, Sabol 2007). That said, it is not necessarily clear how job skills and prior work experience affect labor market prospects for those on parole. For example, when considering the changing nature of the labor market, the most experienced workers may not necessarily be the best equipped to adapt to a new labor market. Put another way, skills in manufacturing may not necessarily translate to a tech or service economy. We saw some evidence of this pattern when looking at older people on parole who have had more years to gain experience in the labor market but also had more joblessness. At the same time, we could not control for potentially important individual-level factors related to joblessness or home neighborhood location, and thus selection into different neighborhoods may still be an issue (e.g., see Porter and Vogel 2014). The rich literature on parolee mobility limitations suggests this may be less the “selection” of a neighborhood and more of a “push” or “constraint”. Nonetheless, this limits our ability to make causal claims given that parolees may have moved into neighborhoods more structurally disadvantaged, which then results in more joblessness for them. Thus, future research might examine selection in various contexts around the home and work locations of people on parole.

Another limitation is that employers often do not want to hire people on parole for a variety of reasons (Holzer 1996, Pager and Quillian 2005, Pager 2007), and future research will want to test how employers make decisions in hiring, as well as the neighborhoods of these employers. This point also implies another kind of selection effect that is not entirely determined by people on parole, and an arguably important one given this would be a one potential mechanism of competition in the labor market. One possibility to consider for future research is that employers may be more willing to hire a ‘local’ even though they have a criminal record. Nevertheless, these kinds of social ties likely further exclude many people on parole because they do not have access to those networks (see also Pedulla and Pager 2019). An additional limitation is that conclusions may be sensitive to the exclusion of intermediate sanctions because of the way residential spells are measured. Finally, another limitation is that we only focus on when people on parole reported being officially jobless, and future research may want to examine parolees working ‘off the books’ in the informal economy (Loughran et al. 2013).

From a policy perspective, the findings remind us that an individual’s reintegration is not simply a result of what people on parole do, but also potential employers, the spatial distribution of the economic structure, and the conditions of the broader regional labor market (i.e., competition for jobs). We also showed in our supplemental and footnote models that parolees in neighborhoods with more people on parole, those during the Great Recession, and those in neighborhoods linked to job hubs, experience more joblessness, suggesting a potential competition effect or possibly overwhelmed demand for services. This effect implies that increasing competition is likely going to result in worse job prospects, particularly for people of color on parole. Future research might examine whether places with more consolidation of local companies by larger companies has consequences for employment of people on parole. For instance, does the influx of large corporations help or hinder those on parole, rather than smaller local businesses. Even still, this implies a need to consider how much of people's success on parole is driven by factors that are structural and influenced by (a lack of) governmental policy.

Our findings indicate that programs and nonprofits need to have connections to the broader landscape of the region, and possibly even broader spatial scales, and thus cookie cutter policies targeting only one neighborhood are unlikely to be successful (see also Miller 2014, 2021). At the same time, parole officers should also consider structural barriers in addition to focusing on individual characteristics. The racial and ethnic disparities in joblessness are unlikely to be addressed by local programs alone given the extent of the challenges associated with race, poverty, employment, and criminal records in hiring practices.

In this study we have shown that how a person on parole's neighborhood is structurally and spatially positioned within the network of neighborhoods can have consequences for their job prospects. In fact, more incoming and outgoing distant links to other neighborhoods can fundamentally influence access to the labor market. The successful reintegration of people on parole is not simply a function of their own neighborhood or individual characteristics, but how their neighborhood is, or is not, embedded within the broader network of neighborhoods.

Table 1. Summary Statistics

	Total		White		Black		Latino	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Jobless Days	80.93	140.27	65.93	125.24	105.72	162.11	68.19	122.46
Days at Address	265.02	292.37	256.38	286.11	272.81	300.64	264.70	287.37
Neighborhood Unemployment Context and Network of Neighborhood Measures								
% Unemployment	8.92	4.86	7.57	4.03	10.42	5.52	8.75	4.36
Spatial Lag % Unemployment	7.80	2.01	7.22	2.01	8.29	1.90	7.92	1.96
Jobs within 10 miles (logged)	10.19	1.87	9.58	2.04	10.70	1.56	10.32	1.79
Indegree	10.06	16.77	9.28	15.67	10.30	19.51	10.78	14.01
Outdegree	11.19	6.58	9.39	5.97	12.14	6.50	12.32	6.94
Outdegree within 1 mile (micro)	0.23	0.52	0.16	0.44	0.24	0.52	0.31	0.60
Outdegree within 1 to 10 miles (meso)	6.85	5.11	5.35	4.66	7.44	4.77	8.07	5.61
Outdegree beyond 10 miles (macro)	4.11	3.52	3.89	3.50	4.46	3.51	3.94	3.51
People on Parole Characteristics								
Male	0.86	0.34	0.81	0.40	0.90	0.31	0.90	0.30
Age	40.31	10.27	41.20	10.15	40.66	10.42	38.70	10.05
Married	0.17	0.38	0.18	0.38	0.15	0.36	0.18	0.39
Black	0.36	0.48						
Latino	0.27	0.45						
Sentence Length	10.22	11.68	9.05	10.40	12.75	13.70	8.46	9.68
Convicted of Violent Crime	0.18	0.38	0.13	0.33	0.23	0.42	0.18	0.39
Mandatory Release	0.34	0.47	0.35	0.48	0.31	0.46	0.36	0.48
Neighborhood Demographic Characteristics								
Ethnic Heterogeneity	45.52	17.72	45.43	16.11	50.02	16.36	39.53	19.63
% Latino	39.97	27.11	30.63	22.78	33.30	21.85	61.30	27.16
% Black	19.77	24.06	10.76	14.21	37.03	28.14	8.99	13.66
Residential Stability	-0.30	0.97	-0.26	0.86	-0.42	1.08	-0.19	0.92
Population Density per sqr. Mile (rescaled by 1000)	3.24	3.00	2.42	2.67	3.67	3.07	3.74	3.07
Population within 20 miles (logged)	13.40	1.50	13.03	1.53	13.82	1.38	13.33	1.48
% Poverty	22.17	12.96	17.36	11.20	25.28	13.46	24.54	12.56
Spatial Lag Ethnic Heterogeneity	54.52	14.12	52.47	13.67	61.10	9.16	48.42	16.42
Spatial Lag % Latino	38.56	20.70	29.61	16.94	35.83	14.69	54.17	23.25
Spatial Lag % Black	15.12	12.32	11.83	9.56	22.76	13.19	9.37	8.90
Spatial Lag Residential Stability	0.07	0.92	0.13	0.91	-0.13	0.89	0.24	0.92
Spatial Lag Population Density	2.09	1.46	1.59	1.38	2.44	1.45	2.26	1.41
Spatial Lag % Poverty	19.57	7.03	16.76	6.62	20.62	6.13	21.96	7.43
N releases	90395		31590		32640		25670	
N Spells	191824		69514		69165		52216	

Table 2. Multilevel Negative Binomial Regressions for Jobless Days for All People Released on Parole

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)
Neighborhood Unemployment Context and Network of Neighborhood Measures							
% Unemployment	0.0030*	0.0023	0.0031*	0.0036*	0.0030*	0.0030*	0.0030*
	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0014)	(0.0014)	(0.0014)
Spatial Lag % Unemployment	0.0313***	0.0317***	0.0231**	0.0227**	0.0223**	0.0223**	0.0223**
	(0.0070)	(0.0070)	(0.0079)	(0.0079)	(0.0078)	(0.0078)	(0.0079)
Jobs within 10 miles (logged)	-0.0580***	-0.0646***	-0.0608***	-0.0594***	-0.0475***	-0.0473***	-0.0468***
	(0.0158)	(0.0156)	(0.0147)	(0.0148)	(0.0130)	(0.0130)	(0.0125)
Indegree		0.0012***	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Outdegree		-0.0044*	-0.0053**				
		(0.0018)	(0.0018)				
Outdegree within 1 mile (micro)				0.0021	0.0032		0.0032
				(0.0059)	(0.0063)		(0.0064)
Outdegree within 1 to 10 miles (meso)					-0.0093**	-0.0093**	-0.0094**
					(0.0031)	(0.0031)	(0.0032)
Outdegree beyond 10 miles (macro)							0.0004
							(0.0026)
Neighborhood Demographic Characteristics							
Ethnic Heterogeneity	-0.0005	-0.0006	0.0005	0.0006	0.0004	0.0004	0.0004
	(0.0004)	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
% Latino	0.0000	0.0003	0.0013**	0.0009	0.0014**	0.0014**	0.0013**
	(0.0007)	(0.0007)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
% Black	0.0006	0.0007	0.0007	0.0005	0.0008	0.0008	0.0008
	(0.0006)	(0.0006)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Residential Stability	-0.0040	-0.0069	0.0027	0.0116*	0.0038	0.0038	0.0041
	(0.0062)	(0.0086)	(0.0071)	(0.0055)	(0.0070)	(0.0070)	(0.0069)
Population Density	0.0010	0.0043	0.0049**	0.0031	0.0049**	0.0051**	0.0049**
	(0.0026)	(0.0028)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Population within 20 miles (logged)	0.0910***	0.0989***	0.1160***	0.1066***	0.1031***	0.1028***	0.1021***
	(0.0220)	(0.0235)	(0.0220)	(0.0204)	(0.0202)	(0.0201)	(0.0189)

*Table continued on the next page.

% Poverty	0.0036***	0.0042***	0.0035***	0.0028***	0.0036***	0.0036***	0.0036***
	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
Spatial Lag Ethnic Heterogeneity			-0.0042**	-0.0041*	-0.0041**	-0.0041**	-0.0041*
			(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Spatial Lag % Latino			-0.0023	-0.0020	-0.0024	-0.0024	-0.0024
			(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0015)
Spatial Lag % Black			0.0024	0.0026	0.0021	0.0021	0.0021
			(0.0016)	(0.0017)	(0.0016)	(0.0016)	(0.0015)
Spatial Lag Residential Stability			-0.0390	-0.0377	-0.0397*	-0.0397*	-0.0397*
			(0.0200)	(0.0200)	(0.0202)	(0.0202)	(0.0202)
Spatial Lag Population Density			-0.0152	-0.0126	-0.0146	-0.0145	-0.0145
			(0.0145)	(0.0146)	(0.0142)	(0.0142)	(0.0142)
Spatial Lag % Poverty			0.0054	0.0050	0.0058	0.0058	0.0058
			(0.0033)	(0.0034)	(0.0033)	(0.0033)	(0.0033)
People on Parole Characteristics							
Male	-0.2300***	-0.2305***	-0.2307***	-0.2306***	-0.2311***	-0.2311***	-0.2311***
	(0.0183)	(0.0182)	(0.0182)	(0.0183)	(0.0182)	(0.0182)	(0.0182)
Age	-0.0740***	-0.0740***	-0.0740***	-0.0740***	-0.0739***	-0.0739***	-0.0739***
	(0.0037)	(0.0036)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Age Squared	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married	-0.1059***	-0.1052***	-0.1062***	-0.1064***	-0.1062***	-0.1062***	-0.1062***
	(0.0125)	(0.0126)	(0.0126)	(0.0125)	(0.0127)	(0.0127)	(0.0127)
Black	0.2943***	0.2937***	0.2910***	0.2911***	0.2913***	0.2913***	0.2913***
	(0.0125)	(0.0124)	(0.0123)	(0.0125)	(0.0123)	(0.0123)	(0.0123)
Latino	-0.0057	-0.0085	-0.0006	0.0001	0.0014	0.0013	0.0015
	(0.0165)	(0.0170)	(0.0204)	(0.0203)	(0.0201)	(0.0201)	(0.0203)
Years Sentenced	-0.0054***	-0.0054***	-0.0054***	-0.0054***	-0.0055***	-0.0055***	-0.0055***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Convicted of Violent Crime	-0.0393**	-0.0391**	-0.0401**	-0.0404**	-0.0398**	-0.0398**	-0.0398**
	(0.0135)	(0.0135)	(0.0132)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
Mandatory Release	0.1666***	0.1665***	0.1654***	0.1655***	0.1656***	0.1656***	0.1657***
	(0.0080)	(0.0081)	(0.0081)	(0.0081)	(0.0082)	(0.0082)	(0.0081)
Intercept	-0.3454	-0.3721	-0.4369	-0.3667	-0.3990	-0.3969	-0.3948
	(0.2238)	(0.2339)	(0.2293)	(0.2197)	(0.2281)	(0.2273)	(0.2218)
N Spells	191824	191824	191824	191824	191824	191824	191824
Note: ***p < .001, **p<.01, *p< .05							

Table 3. Multilevel Negative Binomial Regressions for Jobless Days with Spatial Degree Measures by Race/Ethnicity of Individual on Parole

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	White	White	Black	Black	Latino	Latino
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)
Neighborhood Unemployment Context and Network of Neighborhood Measures						
Indegree	0.0007	0.0006	0.0010***	0.0009***	0.0019***	0.0019***
	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0005)	(0.0005)
Outdegree	-0.0033		-0.0054***		-0.0077**	
	(0.0025)		(0.0015)		(0.0028)	
Outdegree within 1 mile (micro)		0.0025		0.0054		0.0029
		(0.0123)		(0.0079)		(0.0140)
Outdegree within 1 to 10 miles (meso)		-0.0125***		-0.0080**		-0.0098*
		(0.0033)		(0.0025)		(0.0046)
Outdegree beyond 10 miles (macro)		0.0071*		-0.0016		-0.0039
		(0.0035)		(0.0023)		(0.0041)
N Spells	69514	69514	69165	69165	52216	52216
Note: All measures in Table 2 included as control variables. Full Results in Appendix A. ***p < .001, **p<.01, *p< .05						

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Appendix A. Multilevel Negative Binomial Regressions for Jobless Days with Spatial Degree Measures by Race/Ethnicity of Individual on Parole

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	White	White	Black	Black	Latino	Latino
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)
Neighborhood Unemployment Context and Network of Neighborhood Measures						
% Unemployment	0.0075**	0.0070**	0.0018	0.0018	0.0013	0.0013
	(0.0026)	(0.0025)	(0.0011)	(0.0010)	(0.0020)	(0.0020)
Spatial Lag % Unemployment	0.0269***	0.0247**	0.0182*	0.0179*	0.0186	0.0184
	(0.0078)	(0.0078)	(0.0075)	(0.0076)	(0.0128)	(0.0128)
Jobs within 10 miles (logged)	-0.0469***	-0.0222	-0.0787***	-0.0690***	-0.0898***	-0.0810***
	(0.0142)	(0.0123)	(0.0207)	(0.0191)	(0.0219)	(0.0191)
Indegree	0.0007	0.0006	0.0010***	0.0009***	0.0019***	0.0019***
	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0005)	(0.0005)
Outdegree	-0.0033		-0.0054***		-0.0077**	
	(0.0025)		(0.0015)		(0.0028)	
Outdegree within 1 mile (micro)		0.0025		0.0054		0.0029
		(0.0123)		(0.0079)		(0.0140)
Outdegree within 1 to 10 miles (meso)		-0.0125***		-0.0080**		-0.0098*
		(0.0033)		(0.0025)		(0.0046)
Outdegree beyond 10 miles (macro)		0.0071*		-0.0016		-0.0039
		(0.0035)		(0.0023)		(0.0041)
Neighborhood Demographic Characteristics						
Ethnic Heterogeneity	-0.0001	-0.0002	0.0001	0.0001	-0.0001	-0.0001
	(0.0007)	(0.0007)	(0.0004)	(0.0004)	(0.0007)	(0.0007)
% Latino	0.0011	0.0013	0.0017***	0.0018***	0.0010	0.0010
	(0.0009)	(0.0009)	(0.0005)	(0.0005)	(0.0009)	(0.0009)
% Black	0.0023*	0.0025*	0.0012*	0.0012*	0.0014	0.0015
	(0.0010)	(0.0010)	(0.0006)	(0.0006)	(0.0010)	(0.0009)
Residential Stability	0.0099	0.0104	-0.0017	-0.0013	0.0063	0.0088
	(0.0125)	(0.0129)	(0.0061)	(0.0056)	(0.0130)	(0.0118)
Population Density	-0.0019	-0.0007	0.0011	0.0007	0.0101***	0.0097***
	(0.0051)	(0.0047)	(0.0025)	(0.0024)	(0.0028)	(0.0028)
Population within 20 miles (logged)	0.1071***	0.0823***	0.1169***	0.1077***	0.1325***	0.1243***
	(0.0205)	(0.0177)	(0.0247)	(0.0229)	(0.0285)	(0.0248)
% Poverty	0.0023	0.0027	0.0032***	0.0032***	0.0048***	0.0048***
	(0.0015)	(0.0014)	(0.0007)	(0.0007)	(0.0011)	(0.0011)
Spatial Lag Ethnic Heterogeneity	-0.0037*	-0.0032	-0.0027*	-0.0026*	-0.0048	-0.0047
	(0.0017)	(0.0016)	(0.0011)	(0.0011)	(0.0025)	(0.0024)
Spatial Lag % Latino	-0.0027	-0.0030	-0.0031*	-0.0033*	0.0004	0.0003
	(0.0020)	(0.0020)	(0.0014)	(0.0014)	(0.0025)	(0.0024)
Spatial Lag % Black	0.0026	0.0021	0.0005	0.0003	0.0051	0.0047
	(0.0020)	(0.0019)	(0.0011)	(0.0010)	(0.0034)	(0.0031)
Spatial Lag Residential Stability	-0.0341	-0.0357	-0.0453**	-0.0444**	-0.0819*	-0.0826*
	(0.0266)	(0.0263)	(0.0156)	(0.0156)	(0.0321)	(0.0323)
Spatial Lag Population Density	-0.0043	-0.0006	-0.0079	-0.0085	-0.0247	-0.0237
	(0.0209)	(0.0195)	(0.0134)	(0.0134)	(0.0161)	(0.0160)
Spatial Lag % Poverty	0.0053	0.0062	0.0043	0.0047	0.0037	0.0040
	(0.0040)	(0.0039)	(0.0031)	(0.0030)	(0.0048)	(0.0046)

*Table Continued on the next page

People on Parole Characteristics						
Male	-0.2640***	-0.2652***	-0.0870***	-0.0873***	-0.3218***	-0.3224***
	(0.0225)	(0.0225)	(0.0167)	(0.0167)	(0.0222)	(0.0221)
Age	-0.0538***	-0.0537***	-0.0782***	-0.0781***	-0.0891***	-0.0891***
	(0.0049)	(0.0049)	(0.0058)	(0.0058)	(0.0048)	(0.0048)
Age Squared	0.0007***	0.0007***	0.0009***	0.0009***	0.0011***	0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married	-0.0757***	-0.0753***	-0.0951***	-0.0952***	-0.1655***	-0.1655***
	(0.0179)	(0.0177)	(0.0121)	(0.0120)	(0.0213)	(0.0213)
Years Sentenced	-0.0065***	-0.0066***	-0.0048***	-0.0048***	-0.0044***	-0.0044***
	(0.0009)	(0.0009)	(0.0005)	(0.0005)	(0.0012)	(0.0012)
Convicted of Violent Crime	-0.0194	-0.0194	-0.0819***	-0.0815***	0.0026	0.0027
	(0.0251)	(0.0250)	(0.0124)	(0.0122)	(0.0297)	(0.0300)
Mandatory Release	0.1555***	0.1565***	0.1515***	0.1519***	0.1850***	0.1848***
	(0.0133)	(0.0133)	(0.0124)	(0.0123)	(0.0130)	(0.0131)
Intercept	-0.9065***	-0.8288***	0.0610	0.0825	-0.0201	0.0002
	(0.2355)	(0.2264)	(0.2720)	(0.2692)	(0.2795)	(0.2717)
N Spells	69514	69514	69165	69165	52216	52216
Note: ***p < .001, **p<.01, *p< .05						

Appendix B Multilevel Negative Binomial Regressions for Jobless Days with interactions with population density and population within 20 miles

	Model 1	Model 2	Model 3	Model 4
	Coef.	Coef.	Coef.	Coef.
	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)
Neighborhood Unemployment Context and Network of Neighborhood Measures				
% Unemployment	0.0031*	0.0031*	0.0030*	0.0030*
	(0.0015)	(0.0015)	(0.0015)	(0.0014)
Spatial Lag % Unemployment	0.0231**	0.0232**	0.0230**	0.0229**
	(0.0079)	(0.0079)	(0.0079)	(0.0078)
Jobs within 10 miles (logged)	-0.0602***	-0.0584***	-0.0588***	-0.0526***
	(0.0148)	(0.0141)	(0.0140)	(0.0121)
Indegree	0.0003	0.0011***	-0.0027	0.0011***
	(0.0005)	(0.0002)	(0.0083)	(0.0002)
Outdegree	-0.0054**	-0.0066**	-0.0053**	-0.0402
	(0.0018)	(0.0025)	(0.0017)	(0.0259)
Indegree * Population Density	0.0003			
	(0.0002)			
Outdegree * Population Density		0.0003		
		(0.0003)		
Indegree * Population within 20 miles (logged)			0.0003	
			(0.0006)	
Outdegree * Population within 20 miles (logged)				0.0025
				(0.0018)
Neighborhood Demographic Characteristics				
Ethnic Heterogeneity	0.0005	0.0006	0.0005	0.0006
	(0.0003)	(0.0004)	(0.0003)	(0.0004)
% Latino	0.0013**	0.0013**	0.0013**	0.0012**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
% Black	0.0008	0.0007	0.0007	0.0006
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Residential Stability	0.0034	0.0039	0.0024	0.0075
	(0.0072)	(0.0066)	(0.0074)	(0.0058)
Population Density	0.0029	-0.0007	0.0048**	0.0043**
	(0.0019)	(0.0046)	(0.0016)	(0.0015)
Population within 20 miles (logged)	0.1164***	0.1164***	0.1136***	0.0991***
	(0.0220)	(0.0221)	(0.0209)	(0.0169)
% Poverty	0.0035***	0.0035***	0.0035***	0.0036***
	(0.0008)	(0.0007)	(0.0008)	(0.0008)
Spatial Lag Ethnic Heterogeneity	-0.0042**	-0.0043**	-0.0042**	-0.0044**
	(0.0016)	(0.0016)	(0.0016)	(0.0017)
Spatial Lag % Latino	-0.0023	-0.0022	-0.0023	-0.0023
	(0.0015)	(0.0015)	(0.0015)	(0.0015)

*Table continued on the next page

Spatial Lag % Black	0.0024	0.0024	0.0024	0.0022
	(0.0017)	(0.0016)	(0.0017)	(0.0015)
Spatial Lag Residential Stability	-0.0393	-0.0392*	-0.0390	-0.0427*
	(0.0201)	(0.0200)	(0.0200)	(0.0207)
Spatial Lag Population Density	-0.0166	-0.0154	-0.0163	-0.0256
	(0.0147)	(0.0146)	(0.0143)	(0.0161)
Spatial Lag % Poverty	0.0053	0.0054	0.0054	0.0059
	(0.0033)	(0.0033)	(0.0034)	(0.0033)
People on Parole Characteristics				
Male	-0.2307***	-0.2307***	-0.2306***	-0.2306***
	(0.0182)	(0.0182)	(0.0182)	(0.0181)
Age	-0.0740***	-0.0740***	-0.0740***	-0.0740***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Age Squared	0.0009***	0.0009***	0.0009***	0.0009***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married	-0.1061***	-0.1061***	-0.1062***	-0.1062***
	(0.0127)	(0.0126)	(0.0126)	(0.0126)
Black	0.2909***	0.2908***	0.2910***	0.2907***
	(0.0123)	(0.0122)	(0.0123)	(0.0123)
Latino	-0.0008	-0.0003	-0.0006	0.0010
	(0.0204)	(0.0204)	(0.0204)	(0.0202)
Years Sentenced	-0.0054***	-0.0054***	-0.0054***	-0.0054***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Convicted of Violent Crime	-0.0402**	-0.0401**	-0.0401**	-0.0401**
	(0.0132)	(0.0132)	(0.0132)	(0.0133)
Mandatory Release	0.1653***	0.1654***	0.1654***	0.1655***
	(0.0081)	(0.0081)	(0.0081)	(0.0082)
Intercept	-0.4414	-0.4497	-0.4188	-0.2588
	(0.2292)	(0.2323)	(0.2248)	(0.2130)
N Spells	191824	191824	191824	191824
Note: ***p < .001, **p<.01, *p< .05				

Appendix C Multilevel Negative Binomial Regressions for Jobless Days with Job Flows Measures

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)
Neighborhood Unemployment Context and Network of Neighborhood Measures									
% Unemployment	0.0031*	0.0028	0.0032*	0.0023	0.0034*	0.0030*	0.0031*	0.0028	0.0027
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Spatial Lag % Unemployment	0.0231**	0.0226**	0.0232**	0.0232**	0.0228**	0.0230**	0.0231**	0.0226**	0.0226**
	(0.0079)	(0.0079)	(0.0079)	(0.0080)	(0.0079)	(0.0079)	(0.0079)	(0.0078)	(0.0078)
Jobs within 10 miles (logged)	-0.0608***	-0.0590***	-0.0610***	-0.0663***	-0.0481***	-0.0595***	-0.0610***	-0.0594***	-0.0577***
	(0.0147)	(0.0146)	(0.0148)	(0.0140)	(0.0141)	(0.0149)	(0.0172)	(0.0150)	(0.0151)
Indegree	0.0011***		0.0010***	0.0007***	0.0011***	-0.0026	0.0011***		
	(0.0002)		(0.0002)	(0.0002)	(0.0002)	(0.0049)	(0.0002)		
Outdegree	-0.0053**		-0.0056**	-0.0069***	-0.0080***	-0.0052**	-0.0057		
	(0.0018)		(0.0018)	(0.0017)	(0.0022)	(0.0018)	(0.0122)		
Incoming Commuters (divided by 10)		0.0004***						0.0009	0.0004***
		(0.0001)						(0.0018)	(0.0001)
Outgoing Commuters (divided by 10)		-0.0019***						-0.0019***	0.0008
		(0.0004)						(0.0004)	(0.0040)
Same Neighborhood Commuters			0.0002						
			(0.0002)						
Count of People on Parole in Neighborhood				0.0009**					
				(0.0003)					
Weighted Outdegree (logged)					0.0387***				
					(0.0114)				
Indegree * Jobs within 10 miles						0.0003			
						(0.0004)			
Outdegree * Jobs within 10 miles							0.0000		
							(0.0010)		
Incoming Commuters * Jobs within 10 miles								-0.0000	
								(0.0001)	
Outgoing Commuters * Jobs within 10 miles									-0.0002
									(0.0003)
Neighborhood Demographic Characteristics									
Ethnic Heterogeneity	0.0005	0.0006	0.0005	0.0005	0.0004	0.0005	0.0005	0.0006	0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
% Latino	0.0013**	0.0012**	0.0013**	0.0011**	0.0015***	0.0013**	0.0013**	0.0012**	0.0012**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
% Black	0.0007	0.0006	0.0007	-0.0000	0.0010*	0.0007	0.0007	0.0006	0.0007
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)

*Table Continued on Next Page

Residential Stability	0.0027	0.0016	0.0036	-0.0023	-0.0010	0.0022	0.0028	0.0019	0.0006
	(0.0071)	(0.0064)	(0.0069)	(0.0069)	(0.0074)	(0.0072)	(0.0065)	(0.0065)	(0.0061)
Population Density	0.0049**	0.0056***	0.0051**	0.0062***	0.0047**	0.0045*	0.0049**	0.0057**	0.0061***
	(0.0016)	(0.0016)	(0.0017)	(0.0015)	(0.0015)	(0.0019)	(0.0016)	(0.0018)	(0.0016)
Population within 20 miles (logged)	0.1160***	0.1124***	0.1175***	0.1185***	0.0689***	0.1150***	0.1161***	0.1127***	0.1117***
	(0.0220)	(0.0210)	(0.0224)	(0.0222)	(0.0187)	(0.0221)	(0.0234)	(0.0212)	(0.0212)
% Poverty	0.0035***	0.0037***	0.0034***	0.0032***	0.0045***	0.0035***	0.0035***	0.0037***	0.0037***
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0007)
Spatial Lag Ethnic Heterogeneity	-0.0042**	-0.0042**	-0.0042*	-0.0046**	-0.0041*	-0.0043**	-0.0042*	-0.0041*	-0.0041*
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0017)	(0.0016)	(0.0017)
Spatial Lag % Latino	-0.0023	-0.0022	-0.0023	-0.0018	-0.0024	-0.0023	-0.0023	-0.0022	-0.0022
	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Spatial Lag % Black	0.0024	0.0025	0.0024	0.0030	0.0023	0.0024	0.0024	0.0025	0.0024
	(0.0016)	(0.0017)	(0.0016)	(0.0017)	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0017)
Spatial Lag Residential Stability	-0.0390	-0.0409*	-0.0393	-0.0418*	-0.0341	-0.0389	-0.0390	-0.0409*	-0.0409*
	(0.0200)	(0.0200)	(0.0201)	(0.0189)	(0.0190)	(0.0199)	(0.0202)	(0.0201)	(0.0201)
Spatial Lag Population Density	-0.0152	-0.0181	-0.0149	-0.0144	-0.0110	-0.0166	-0.0154	-0.0176	-0.0150
	(0.0145)	(0.0146)	(0.0144)	(0.0146)	(0.0139)	(0.0143)	(0.0148)	(0.0145)	(0.0153)
Spatial Lag % Poverty	0.0054	0.0054	0.0055	0.0044	0.0062	0.0054	0.0054	0.0054	0.0053
	(0.0033)	(0.0034)	(0.0033)	(0.0034)	(0.0034)	(0.0034)	(0.0033)	(0.0034)	(0.0034)
People on Parole Characteristics									
Male	-0.2307***	-0.2307***	-0.2308***	-0.2300***	-0.2316***	-0.2306***	-0.2307***	-0.2308***	-0.2307***
	(0.0182)	(0.0183)	(0.0182)	(0.0177)	(0.0183)	(0.0182)	(0.0182)	(0.0184)	(0.0183)
Age	-0.0740***	-0.0740***	-0.0740***	-0.0741***	-0.0740***	-0.0740***	-0.0740***	-0.0740***	-0.0740***
	(0.0035)	(0.0035)	(0.0035)	(0.0036)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Age Squared	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married	-0.1062***	-0.1062***	-0.1061***	-0.1046***	-0.1060***	-0.1062***	-0.1062***	-0.1062***	-0.1063***
	(0.0126)	(0.0126)	(0.0126)	(0.0128)	(0.0127)	(0.0126)	(0.0126)	(0.0126)	(0.0127)
Black	0.2910***	0.2919***	0.2906***	0.2945***	0.2905***	0.2911***	0.2910***	0.2919***	0.2920***
	(0.0123)	(0.0124)	(0.0121)	(0.0112)	(0.0122)	(0.0123)	(0.0122)	(0.0124)	(0.0124)
Latino	-0.0006	0.0004	-0.0009	0.0049	-0.0001	-0.0006	-0.0006	0.0004	0.0001
	(0.0204)	(0.0204)	(0.0203)	(0.0206)	(0.0205)	(0.0204)	(0.0204)	(0.0204)	(0.0205)
Years Sentenced	-0.0054***	-0.0054***	-0.0054***	-0.0055***	-0.0054***	-0.0054***	-0.0054***	-0.0054***	-0.0054***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Convicted of Violent Crime	-0.0401**	-0.0399**	-0.0403**	-0.0389**	-0.0403**	-0.0401**	-0.0401**	-0.0399**	-0.0398**
	(0.0132)	(0.0132)	(0.0132)	(0.0129)	(0.0131)	(0.0132)	(0.0132)	(0.0132)	(0.0132)
Mandatory Release	0.1654***	0.1652***	0.1654***	0.1659***	0.1653***	0.1654***	0.1654***	0.1652***	0.1651***
	(0.0081)	(0.0081)	(0.0081)	(0.0083)	(0.0082)	(0.0081)	(0.0081)	(0.0081)	(0.0081)
Intercept	-0.4369	-0.4152	-0.4638*	-0.4050	-0.6010*	-0.4271	-0.4358*	-0.4179	-0.4266
	(0.2293)	(0.2252)	(0.2328)	(0.2440)	(0.2553)	(0.2287)	(0.2217)	(0.2254)	(0.2222)
N Spells	191824	191824	191824	191824	191821	191824	191824	191824	191824
Note: ***p < .001, **p<.01, *p< .05									