Reconceptualizing neighborhoods of marginal men:
A new measure of spatial exposure

Neighborhoods are considered critical sites of sociological and demographic processes that serve as places of collective socialization, peer group interaction, and resource allocation (Sampson, et al. 2002). Among poor and marginalized men—in this paper, men recently released from prison—neighborhoods with high levels of violence, unemployment, and poverty are not only consequential for social and economic outcomes but are also risk factors for future criminal behavior (Harding, et al. 2013; Kubrin and Stewart 2006; Petersilia 2003). Despite the conceptual importance of neighborhoods, their definition and measurement have proven difficult. Moreover, current methodological approaches may be ill-suited to highly mobile, marginalized groups. In this paper, we utilize novel GPS-coordinate data to propose a new measure of neighborhoods based on daily exposure time. We use this approach to answer three questions:

- *Q1: What neighborhoods are most frequented by men recently released from prison? Are residential addresses good measures of where they spend most of their time?*
- *Q2: What are the characteristics of these areas? Are these areas more or less advantaged compared to areas based on residential addresses?*
- *Q3: What are the functions of these areas? Are more advantaged areas associated with particular activities and processes, e.g., do they provide institutional capacities through employment or peer group influences through visiting family and friends?*

I. BACKGROUND

Upon leaving prison, individuals return to neighborhoods that are economically disadvantaged; this is particularly true among black parolees, where nearly 70 percent return to high-poverty areas (Harding et al. 2013). Research that examines neighborhood context after prison typically combines census characteristics with residential address (Harding et al. 2013; Kubrin and Stewart 2006) or county of sentencing (Sabol 2007). These measures may be appropriate if individuals are isolated to areas around their residence (Wilson 1996, 2012) and have stable addresses. However, men recently released from prison experience high residential mobility, housing insecurity, and homelessness (Geller and Curtis 2011; Harding et al. 2013), suggesting that static measures are incomplete portraits of spatial context.

Outside the prisoner reentry literature, some demographers and human geographers call for more precise measurements of neighborhood exposure, arguing that residential address does not account for (1) other neighborhoods encountered in routine activities, (2) the timing and duration of exposure to different neighborhoods, and (3) the functions of different neighborhoods for certain populations (e.g., employment, unstructured socializing, etc.) (Kwan 2012; Matthews 2011; Matthews and Yang 2013).

In response, several recent methodologies move beyond residential neighborhoods to examine “activity spaces,” or the spaces individuals visit in their regular routines. There are various approaches to operationalizing activity spaces. The first approach uses census boundaries of routine destinations such as work, child care, and home, as well as those encountered en route (Jones and Pebley 2014). Since destinations are predefined by researchers based on assumptions of typical routine activities among a general population, this approach may be inappropriate for groups with irregular employment, severed family ties, and unstable housing (Turney and Wildeman 2013; Geller and Curtis 2011). Other approaches define spatial areas by the pathways or polygons individuals make or the areas around their respective blocks (Hipp and Boessen 2013; Palmer et al. 2013; Zenk et al. 2011). Other scholars argue for the incorporation of social network methods into neighborhood definitions (Browning and Soller 2014; Graif et al. 2014; Hipp et al. 2012). All of these methods offer various potential advantages over static residence and activity space measures; however, there are also weaknesses, some of which are specific to studying poor, marginal groups: they have only begun to be empirically tested (Browning and Soller 2014; Graif et al. 2014; Hipp and Boessen 2013; Palmer et al. 2013); they rely on respondent social networks (Hipp et al. 2012), which may be inappropriate for groups with weak network ties; or they diverge from census-defined aggregations (Zenk et al. 2011), preventing analyses of geographic-level demographic, social and economic characteristics that are considered important mechanisms in the neighborhood-effects literature.

In this paper, we develop a new method of conceptualizing neighborhoods in order to examine the characteristics and functions of geographic contexts frequented by a population of marginalized, disadvantaged men. Our measure improves upon existing approaches in three ways. First, we do not begin with a priori, researcher-defined categories for activity spaces. Second, we consider *all* daytime neighborhood exposure, with careful attention to timing, duration, and function. Third, we retain census-defined neighborhood boundaries in order to assess demographic, social, and economic characteristics.

II. DATA, MEASURES, AND METHODS

We analyze data from the Newark Smartphone Reentry Project (NSRP). NSRP participants were sampled from a complete census of eligible parolees released from prison to Newark, New Jersey between April 2012 and April 2013. Parolees were eligible to participate if they were male, recently released from prison, searching work, and neither gang-identified nor convicted of a sex offense. Of the 152 individuals contacted, 135 people (89 percent) agreed to participate in the study.

Participants were given smartphones with a data-collection application created for the project and were followed through the phones for three months. Over this period, participants passively sent GPS information every 15 minutes during daytime hours (8 a.m. to 6 p.m.) and completed smartphone surveys, which were sent daily at randomly-sampled time periods ("experience sampling surveys"). Although many of the participants spent some time out of state during the study period, we limit our sample to data collected within the state of New Jersey. This represents more than 357,000 GPS data points falling within 2,551 census block groups. Each data point is associated with a specific location in space and time and can be matched to experience sampling survey data describing where the respondent was, what he was doing, and with whom.

In order to examine the characteristics of neighborhoods frequented by parolees, including their specific functions in the lives of these men, we develop a summary index that refers to a neighborhood's level of use for a specific population. This measure, which we call *neighborhood spatial exposure* is simply the mean percentage of time respondents spend in a given neighborhood. For example, if respondents *a*, *b*, *c*. . . *N* each spend *t* time of their *T* total participation time in Neighborhood *x*, the spatial exposure (NSE) index would be constructed as follows:

1. $$\mathbf{NSE}_x = \frac{\left(\frac{t_a}{T_a} + \frac{t_b}{T_b} + \frac{t_c}{T_c} + \cdots + \frac{t_N}{T_N}\right)}{N} \cdot \mathbf{100}$$

Thus, a minimum NSE of 0 would imply that Neighborhood *x* was never visited by anyone in the population, and a maximum NSE of 100 would imply that everyone in the population spent all of their time in Neighborhood *x*. In this paper, we use census block groups as neighborhood boundaries, but any geographical unit could be employed.

A similar index could be constructed if we conceptualize parolee neighborhoods as a network (Graif et al. 2014) in which neighborhoods represent nodes and ties represent common respondents (for example, Neighborhood *x* would share a tie with Neighborhood *y* if Respondent *a* visited both), or in a bipartite network, in which nodes represent neighborhoods and respondents and the ties between them represent visits. In both instances, counting the number of ties per node would represent a version of what social network scholars call "degree centrality" (Borgatti, et al. 2013). We feel NSE is more appropriate because it accounts for both variation in *t* (for example, Respondent *a* regularly attends religious services in Neighborhood *x*, but Respondent *b* visited the same neighborhood only once for a job interview) and variation in *T* (for example, Respondent *b* is rearrested after only two months of participation time).

III. RESULTS

We first assess whether residential address is a comprehensive measure of spatial exposure. Although parolees spent substantial amounts of time during the day in their residential neighborhoods (33 percent), spatial exposure varied by individual (see Figure 1). Some individuals spent very little to no time in the block group of their self-reported residence and others spent nearly all of their time in their block group. This suggests the need for a neighborhood measure (NSE) that accounts for individual variability and nonresidential neighborhood exposure.

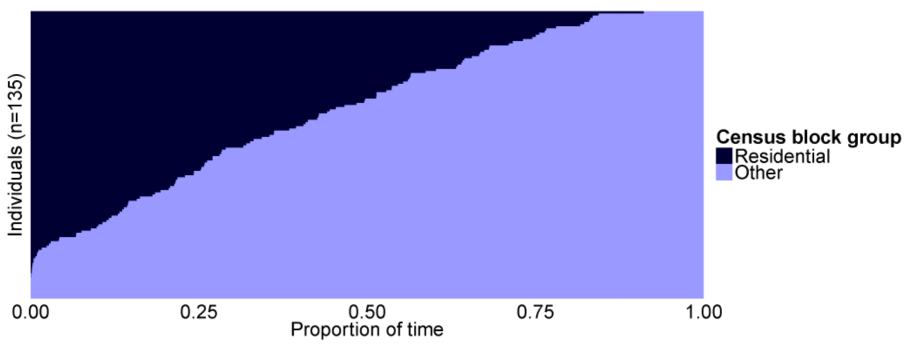

Figure 1: Geographic locations during daytime hours, by individual and census block group

When we apply the NSE index to our full sample of N = 2,551 block groups, we see a much broader geographic range of neighborhoods than might be expected given residential address and prior research on spatial isolation (see Figure 2). Across the sample, the NSE index is a skewed distribution ranging from 0.0002 to 2.7009, with a mean of 0.0392. Although many of the most "central" neighborhoods are block groups of residential address, several represent locations of parole offices and reentry programs. Other central neighborhoods have no apparent function, and the future part of our study will examine the specific characteristics and functions of these other areas based on self-report answers from the experience sampling surveys.

To examine non-residential neighborhoods more carefully, we remove residential block groups (n = 102) from our sample and compute NSE based on non-residential neighborhoods. We then divide the distribution into even quartiles (about 612 neighborhoods each). The resulting groups range from the first 25 percent of block groups (Q1, NSE below 0.0008) to the fourth 25 percent (Q4, NSE between 0.01 and 5.16).

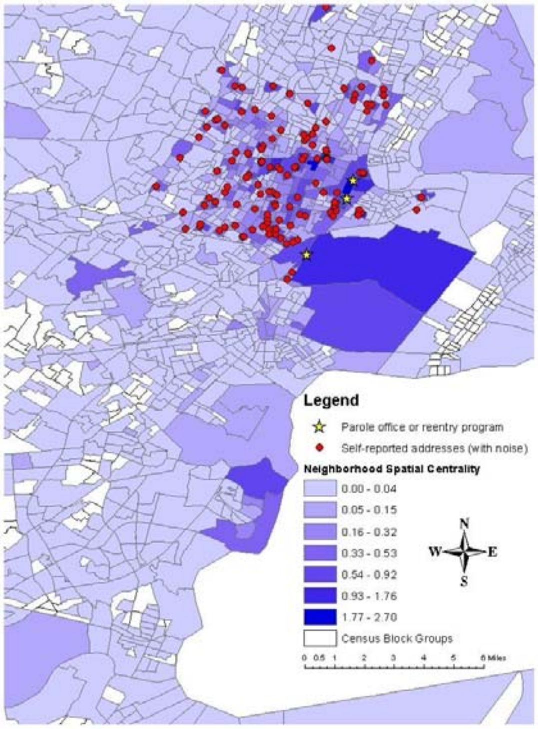

Figure 2. Neighborhood Spatial Exposure for Parolees in Newark, NJ

Using these NSE quartiles, we are able to describe the characteristics of central non-residential block groups and compare them to residential block groups, even without self-reports from survey data. As shown in Figure 3, residential neighborhoods are the most disadvantaged across a range of characteristics, including the prevalence of family poverty, female-headed households, low educational attainment, and unemployment. As parolee concentrations in areas decrease, the neighborhoods are comparably advantaged. This suggests that research that relies on residential address to capture overall neighborhood or spatial exposure over-emphasizes the disadvantaged contexts of residential neighborhoods.

The findings of Figure 3 stand in contrast to other research on the geographic contexts of poor and marginalized groups, which finds that non-residential neighborhoods are disadvantaged similarly to residential areas (Jones and Pebley 2014). We suggest that our conclusions disagree due to different methodological approaches, where previous research asked about predefined categories of interest—e.g., shopping, school, and work. We suggest that neighborhoods can serve multiple functions, including rarely discussed leisure activities (Graif, et al. 2014) and hanging out with friends and family. In the final results section of our paper, we will analyze self-reported answers about activities and social interactions from the experience sampling surveys to identify neighborhoods with functional definitions.

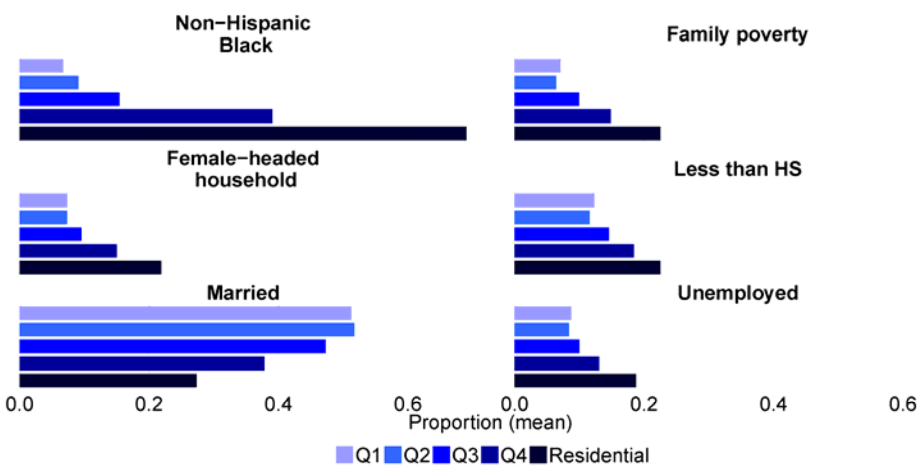

Figure 3: Characteristics of census blocks, by residential address and spatial exposure
Notes: Q1 refers to the characteristics of census blocks that are in the 25 percent of block groups with the lowest neighborhood spatial exposure.

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