Daytime Locations in Spatial Mismatch:
Job Accessibility and Employment at Reentry from Prison

ABSTRACT: Individuals recently released from prison confront many barriers to obtain employment. One potential obstacle is spatial mismatch—or the concentration of low-skilled, non-white jobseekers within central cities and the prevalence of relevant job opportunities in outlying areas. Prior research has found mixed results about the importance of residential place for reentry outcomes. In this paper, we propose that residential location matters for finding work, but this largely static measure does not capture the range of geographic contexts that individuals inhabit throughout the day. We combine novel, real-time GPS information on daytime locations and self-reported employment collected from smartphones with sophisticated measures of job accessibility to test the relative importance of residential and nonresidential spatial mismatch. Our findings suggest that the ability of low-skilled, poor, and urban individuals to compensate for their residential deficits by traveling to nonresidential job clusters is an overlooked and salient consideration in spatial mismatch perspectives.

Over 600,000 people leave prison every year (US Department of Justice 2015). The employment outcomes for these individuals are often poor, due to a variety of factors related to both their pre-prison characteristics and reentry circumstances, including limited education and employment experience, legal restrictions on certain occupations, and criminal record stigma (Holzer, Raphael, and Stoll 2004; Pager 2007a; Western 2006). Individuals recently released from prison are disproportionately low-income and non-white, and they often return to disadvantaged neighborhoods within central cities, where job opportunities tend to be scarce (Harding, Morenoff, and Herbert 2013; Sampson and Loeffler 2010). This paper examines the extent to which spatial mismatch from employment opportunities (Kain 1968) affects finding work for men on parole in the Newark, New Jersey area. We not only analyze spatial mismatch based on self-reported residential address, but we also use novel GPS measures collected from smartphones to assess whether daytime locations and mismatch is associated with employment.

Prior research has analyzed the consequences of spatial mismatch for recidivism among recently released individuals. However, this work has focused exclusively on parolees' residential locations (Bellair and Kowalski 2011; Chamberlain, Boggess, and Powers 2014). Residential locations are subject to measurement error given high rates of mobility and residential instability often experienced at reentry (Harding, Morenoff, and Herbert 2013). Moreover, prior scholarship often assumes that the inability to find employment mediates associations between spatial mismatch and recidivism, though it is not often directly observed or measured. Although our paper extends previous research by directly examining employment outcomes at reentry, our key contribution is that we consider whether daily geographic travel ameliorates or exacerbates residential spatial mismatch experienced by recently released individuals. We consider daily geographic context using high frequency, novel GPS data passively collected from smartphones, which were carried by individuals throughout their first three months after release from prison.

This paper considers the reentry experiences of 131 parolees released to the Newark Parole Office in 2012 and 2013. We examine the role of residential job accessibility for employment outcomes and find that residential spatial mismatch lengthens time to employment, particularly when considering low-skilled and low-income jobs. However, job accessibility based on daytime locations is more consequential for finding work. On their face, these findings might appear rather obvious—if individuals go where the jobs are, they are more likely to find work. However, in practice, timely information on available jobs at specific businesses is hard to come by, and many opportunities become known through social networks (Calvó-Armengol and Zenou 2005). Given their crime and incarceration histories, social networks of parolees are thought to provide lower levels of employment support (Hagan 1993; Sullivan 1989), and reentering individuals may not know where to look for work. Further, there are extensive search costs involved when available jobs are not proximate to where individuals live (Stoll 1999), and prior research on nonresidential locations suggests that poor individuals often travel to places that are similarly disadvantaged to their residential neighborhoods (Krivo et al. 2013). Taken together, this literature suggests that individuals recently released from prison often lack relevant information on job openings, are geographically restricted, and are unable to travel to appropriate areas to find work.

In contrast, our findings highlight the importance of nonresidential daytime locations and we propose that previous scholarship on spatial mismatch overemphasizes the consequences of residential locations. We recommend that parole offices and reentry organizations focus on job clusters, which are fairly stable compared to job opening information, and find ways to connect parolees to known clusters through increasing transportation options. More broadly, we suggest that these findings support the notion that individuals can and do travel outside of their residential areas to access resources. Our measures of daytime location capture the proportion of time that individuals spend in locations with varying levels of job accessibility. The intensity with which individuals spend their time in highly job accessible areas is positively associated with faster procurement of employment. Although we cannot control for the fact that those that are more likely to spend time in job-rich areas may also be more employable, we can say that this time spent appears to pay off in terms of employment outcomes.

Spatial mismatch

Research on spatial mismatch[1] evaluates the extent to which low-income and/or minority households are spatially isolated from employment opportunities, and whether this isolation negatively affects employment outcomes. The spatial mismatch hypothesis was developed by John Kain (1968) in an attempt to highlight one of the tangible effects of the flight of jobs and higher-income and white households from central cities to the suburbs. Kain observed that low-income and minority households were increasingly finding themselves isolated in central cities away from job growth, and that this was one of the causes of widespread inner-city joblessness. William Julius Wilson later reinforced this notion in his influential book *The Truly Disadvantaged* (1987).

Empirical conclusions on whether low-income and minority households are spatially isolated from employment are somewhat inconsistent, but there is compelling evidence that in many U.S. metropolitan areas, the growth of employment on the suburban fringe at the expense of the urban core meant that these households were less likely to be located near areas of strong

[1] For a full review of the literature on spatial mismatch, see (Ihlanfeldt and Sjoquist 1998) and (Kain 1992; Kain 2004).

employment growth. Scholars have found consistent evidence for spatial mismatch in areas as diverse as Los Angeles (Stoll 1999; Blumenberg and Ong 1998; Johnson 2006), Washington, D.C. (Stoll 2006), the Bay Area (Raphael 1998), Atlanta, Boston, and Detroit (Johnson 2006). This research finds that low-income and minority households generally live farther away from employment opportunities and job destinations than white and higher income households, and they must spend more time and travel farther to search for work. Further, using strong empirical techniques that tackle the thorny issue of selection bias in terms of spatial location and employable attributes, this research concludes that spatial proximity matters a lot for actual employment and earnings outcomes.

As spatial analysis techniques have advanced, our understanding of spatial mismatch among central city households has become more nuanced. Shen (1998; 2001) found that job accessibility is actually better among central city households in the Boston Metropolitan Area. Further, Cervero, Sandoval, and Landis (2002) found no relation of regional job accessibility for employment outcomes among welfare recipients in Alameda County, California. Moreover, Sanchez, Shen, and Peng (2004) found no effect from increased transit access on employment outcomes for Temporary Assistance to Needy Families (TANF) participants in the Atlanta, Baltimore, Dallas, Denver, Milwaukee, and Portland metropolitan areas. The techniques pioneered by Shen are utilized in this paper.

Spatial mismatch and reentry from prison

For individuals recently released from prison, spatial mismatch has been considered a primary barrier for finding employment and preventing recidivism (Morenoff and Harding 2014). Reentering individuals tend to live in some of the most geographically isolated and disadvantaged areas, with high rates of unemployment, crime, and poverty (Harding, Morenoff, and Hebert 2013; Sampson and Loeffler 2010). Although the difficulties of finding work for individuals living in these regions are already considered severe, reentering individuals are even more vulnerable to these challenges because of the myriad of obstacles to employment that they experience after prison (Morenoff and Harding 2014). Individuals with felony convictions and prior incarcerations face acute employer stigma, which is further intensified among minority jobseekers (Pager 2003, 2007b; Pager, Western, and Sugie 2009; Holzer, Raphael, Stoll 2007). They may have fewer social connections to work opportunities (Hagan 1993; Sullivan 1989) and limited resources to travel to job openings outside the central city (Pager 2007b). Even apart from their conviction and imprisonment, reentering individuals typically have little work experience and low human capital skills. Indeed, a recent review of individuals returning from prison found that the majority (54 percent) did not have a high school degree (Raphael 2011).

There is very little research on the importance of spatial mismatch for employment at reentry. To the authors' knowledge, only one previous study has examined the role of local labor market conditions on individual employment after release from prison (Sabol 2007). This work found that local county unemployment rates were negatively associated with time to employment. The study is an important contribution to reentry scholarship, since scholars sometimes suggest that local labor market conditions may not matter for reentering individuals, who are often so marginalized from the formal market that fluctuations in demand may not be consequential (for a discussion, see Sabol 2007 and Raphael and Weiman 2007). At the same time, however, the research used broad measures of local job accessibility, imprecise measures of residence (county of sentencing as opposed to release), and limited measures of employment, which were restricted to jobs covered by unemployment insurance. These are critical restrictions, particularly in the reentry realm, since individuals do not necessarily return to their previous county of residence at release (Harding et al. 2013), and the majority of jobs obtained by reentering individuals are off-the-books and temporary (Western and Jacobs 2007).

Closely related research that examines local labor markets and criminal offending suggests that spatial mismatch has implications for recidivism at reentry. In these studies, finding employment is not directly measured but is hypothesized as the main factor mediating the observed associations between local labor market conditions and recidivism rates. In a study of parolees in California, Steven Raphael and David Weiman found that local unemployment rates were positively associated with return to custody, particularly for individuals with a lower risk of violations (2007). Other work by Xia Wang, Daniel Mears, and William Bales also found that local unemployment rates were associated with violent offending, and that these relationships differed by race and industry (2010). Although the above studies considered unemployment rates as measures of job accessibility, a recent study of parolees in Ohio used more precise measures of local job access to examine recidivism rates (Chamberlain et al. 2014). In contrast to previous scholarship, they find that greater job access is related to higher rates of recidivism. Although their measures of job accessibility are more complex than simple unemployment rates and consider distances to jobs and per capita factors, their measures have limitations that may explain the authors' unexpected findings. Specifically, the authors account for distance by counting the number of jobs within fixed boundaries, as opposed to using distance decay functions, which treat distance more appropriately as a continuous factor. Further, they control for competition for work by dividing by the total local population, instead of considering only eligible workers and relevant competitors. Although these considerations may seem minor, we suggest that they can have large ramifications, particularly in disadvantaged urban areas with higher concentrations of businesses and lower proportions of labor force participants.

Throughout all of this research, spatial mismatch and local labor market context is theorized at the residential level, without regard to geographic mobility and nonresidential labor markets. This is not only a critical methodological limitation, but it excludes a salient dimension of spatial life, particularly for those groups whose residential neighborhoods lack organizational resources and job opportunities. The importance of nonresidential routines and locations is increasingly being highlighted, particularly in research that considers "activity spaces." This growing area of scholarship emphasizes the conceptual and methodological limitations of using residential neighborhood as a measure of contextual exposure (Krivo et al. 2013; Kwan 2012; Matthews and Yang 2013; Jones and Pebley 2014; Palmer et al. 2013). In this research, residential neighborhood is only one of the numerous other locations encountered by individuals throughout their daily routines. Incorporating these ideas into spatial mismatch perspectives not only more accurately reflects the range of contexts that individuals inhabit but it also suggests that individuals may compensate for their residential disadvantages through mobility and travel to other locations.

Our paper improves upon previous research on spatial mismatch, employment, and prison reentry by examining the daily geographic contexts of individuals through smartphone-based GPS location data, and by creating measures of job density for areas where individuals spend their time. In addition, we calculate job accessibility measures for their residential locations, weighted by distance and relevant competitors. We also base our employment measures on real-time, smartphone-based self-reports, which include off-the-books and temporary work, and other jobs that are not captured in administrative records but are highly relevant to employment reentry experiences.

Data, Measures, and Methods

In addition to real-time GPS location and daily employment information, this paper considers data from a variety of sources, including interviews, administrative records on criminal justice history, and U.S. Census Bureau information on job openings. The majority of the data come from the Newark Smartphone Reentry Project (NSRP), which followed men recently released from prison for three months each. NSRP participants were sampled from a complete census of all eligible parolees released from prison to the Newark parole office between April 2012 and April 2013. Individuals were eligible to participate if they were searching for work and neither gang-identified nor recently convicted of a sex offense. 89 percent of the 152 individuals contacted (or N=135) agreed to participate in the study. Our final sample is 131, as we exclude four individuals that completed smartphone surveys on two or fewer days. A comparison of demographic and criminal justice characteristics among participants, those not contacted for the study but released from prison around the same time, and those that declined participation revealed no significant differences (Sugie 2014). After an initial interview, participants received smartphones with a data collection application created for the project, and they were followed for three months through the phones.

The smartphone application passively collected GPS location information from participants every 15 minutes during daytime hours (8am to 6pm), producing voluminous and precise data on individuals' locations. Location estimates were collected 87 percent of the expected time. Approximately 6 percent of estimates were not collected because of GPS service disruptions or because the master GPS controls on the smartphones were disabled (we are not able to distinguish between these two conditions). An additional 7 percent of location estimates were not collected because participants had turned off the function on their NSRP smartphone application. Examining these time periods revealed no apparent patterns by day of the week or time of the day (Sugie 2014). For this paper, we consider location estimates within New Jersey. Our final analysis sample includes a large and detailed dataset of 354,691 passively observed GPS location estimates, which refer to 2,508 census block groups (or 40 percent of all New Jersey block groups).

Measures

Employment. We consider two outcome measures of employment, which are created using real-time, self-reported smartphone survey answers. The first measure reflects the number of days of employment over the three-month period, and is the proportion of the days reported working out of the total number of observed days. The second measure concerns the number of days until the first day of work, for use in survival models.

These person-day measures of employment are based on answers from two smartphone surveys that were sent to participants daily. The first survey was an "experience sampling" survey, which was sent to participants' phones at a random time between the hours of 9am and 6pm daily and asked about activities that were occurring at that moment. The second was a daily retrospective survey, which was sent to participants at 7pm daily and solicited information about events and activities throughout the day. If a participant reported working on either of these surveys, we code him as being employed on that day. Using this approach, there is information on daily employment for 84 percent of total observed days in the study. We discuss our approach for handling missing data in the methods section.

Employment Accessibility Measures. Our employment accessibility measures are derived from data from the Longitudinal Employer-Household Dynamics (LEHD) files, produced by the U.S. Census Bureau. We use files from 2009 to 2011 in order to estimate job openings in 2011.

These files include jobs per block group, contain information on North American Industry Classification System (NAICS) codes, and are split into three income categories as well as whether the employee was a college graduate or not.

For an in-depth discussion of how the employment accessibility estimates are created for small levels of geography, see Lens (2014) and Shen (1998, 2001). In sum, the first objective is to estimate nearby job openings for each block group. To do this, we use the total number of jobs that are currently occupied in 2011 and the growth rate in jobs from 2009 to 2011 in order to estimate openings in 2011. Following Shen (1998 and 2001), we assume a turnover rate of 3 percent, multiply that by the number of total jobs ($O_{jt}(T)$) and add that to job openings from growth ($O_{jt}(G)$), using the growth rate from 2007 to 2009:

$$(1)\ O_{jt} = O_{jt}(G) + O_{jt}(T)$$

Using O_{jt}, we weigh each job in inverse proportion to the distance from a block group. To do this, we use a distance-decay function similar to that used by Parks (2004):

$$(2)\ A_i = \sum_{j=1}^{N} O_{jt} \exp(\gamma d_{ij})$$

Here, A_i gives us the distance-weighted job openings for each block group, (d_{ij}) is the distance between the centroid of that block group and every block group within 50 miles, O_{jt} is the number of job openings in every one of those block groups, and γ is a distance decay parameter calculated for a similar population by Parks (2004).[2]

Finally, we need to adjust these estimates to take into account the fact that jobseekers have competition for job openings. To do this, we divide the number of distance-weighted job openings (A_i) by the number of individuals near that block group. As with jobs, we use a distance-decay function, where Equation (2) is applied to the number of unemployed individuals. The farther those households are from the residential block groups of interest, the less weight they carry in the job-openings denominator. Given parolees are likely to be concentrated among areas with unemployed households, the use of this denominator greatly reduces their observed job accessibility when compared with the use of other potential denominators, such as the entire labor force (the employed and those seeking work).

Using this approach, we consider two measures of job accessibility. The first is the job openings measure that accounts for distance and competition, as described above. This job accessibility measure is combined with a participant's residential census block group to capture the distance-weighted number of job openings within 50 miles of the individual's residence. The second measure assesses job accessibility for daytime locations and combines the non-weighted measure (O_{jt} above in Equation 1) with GPS data on daily travel to estimate a daily running average of daytime job accessibility. For these GPS-based daytime measures, we do not weight by the distance decay function in Equation 2 because we are interested in the density of available

[2] Parks (2004) empirically estimated this parameter using household level data on employment and residential locations for low-skilled females and arrived at an estimate of -0.058. With that, her estimate weighs jobs at k distance from block group i by 0 minutes = 1, 5 minutes = .75, 10 minutes = .56, and 20 minutes = .31. Using national surveys, I estimate that the distance to time ratio for commuting to be approximately 3 to 1. That is, roughly the same proportion of people work 15 minutes away that work 5 miles away, 30 minutes corresponds to 10 miles, etc. Thus, I arrived at a decay parameter of -0.058*3 = -0.174, where 0 miles = 1, 3 miles = .59, 5 miles = .42, 15 miles = .07, 30 miles = .005, and 50 miles = .0002. Only jobs within 50 miles are included.

job openings in each specific block group, as opposed to openings within 50 miles of that group. We use different variations of these two measures of residential and nonresidential job accessibility throughout the models. Our main models consider all jobs openings; however, it is likely that men on parole are seeking particular types of employment, such as low-skilled or low-wage work or jobs that do not require college degrees. In additional models, we use job accessibility measures that are restricted to these types of jobs. In all instances, job accessibility measures are standardized, where the sample mean is 0 and the standard deviation is 1.

Other characteristics. We include a rich array of demographics, reentry characteristics, and pre-incarceration characteristics. Demographic and reentry information consider age, race, educational attainment, relationship status, number of children, self-reported health, length of most recent incarceration, and living in a shelter at reentry.[3] We also include a scale of perceived social support, which is based upon the Fragile Families and Child Wellbeing survey, and is the sum of the following five questions: *if you needed assistance during the next three months, could you count on someone to: loan you $200? Loan you $1000? Provide you with a place to live? Help you get around if you needed a ride? Help you when you're sick?*

Pre-incarceration measures include employment history (measured as any formal labor market job) and a variety of criminal-justice factors, such as age at first incarceration, number of previous convictions, incarcerations, and any previous felony conviction. The criminal justice measures come from administrative records from the New Jersey Parole Board, and refer to events that occurred in the state of New Jersey. The other information comes from the initial interview.

[3] Information for number of children is missing for one participant and is replaced using the sample mean.

Methods

We first examine the locations of job openings and the daytime locations of men on parole. This fine-grain descriptive detail is important, since we know relatively little about the extent of geographic mobility among individuals recently released from prison.

We then estimate a series of regression models to identify the associations among residential job accessibility, daytime locations, and employment. First, we examine how residential and daytime location-based job accessibility is associated with the number of days employed. We estimate OLS regression models, where the outcome is the proportion of days employed over the study period. We use a complete-case approach, and we aggregate our measures over the entire study window.

Although the OLS models describe how job accessibility is associated with employment over the study period, the estimates reflect accessibility both prior to and after finding employment. Since places of employment are related to location-based accessibility measures, we next estimate survival models to account for endogeneity and to examine how residential and nonresidential job accessibility is related to time to first day of work.[4] We use a Cox proportional hazards approach to estimate survival models with residential job accessibility and daytime location measures (Cox 1975; Singer and Willett 2003). Cox regression models are continuous time survival approaches that use a partial likelihood method to estimate associations between covariates and a baseline hazard to the outcome (in this case, employment). As a nonparametric model, the approach does not require *a priori* modeling assumptions of the

[4] These models are single decrement approaches, meaning that they estimate only one way of leaving the "at-risk" state for employment, by finding work. However, individuals may also leave the project due to recidivism back to jail or prison. An analysis of criminal justice records suggests that four of the 131 participants may have left the project due to re-incarceration. Because of the relatively low risk of recidivating during the study period, we suggest that the single-decrement approach is preferable.

functional form of the hazard. In order to handle ties, or the occurrence of outcomes at the same time, we use the efron method, which is a good approximation of the more computationally-intensive exact approach (Singer and Willett 2003).

The analysis of detailed, person-day information on employment, daytime locations, and job accessibility provides a novel test of spatial mismatch at reentry; at the same time, however, smartphone data are often characterized by higher rates of missing information for any particular day (Walls and Schafer 2005). Although we have relatively good data coverage, 16 percent of person-days are missing employment information. In Cox regression models, the actual event time to the outcome is less important than the rank order of when individuals experience the outcome (or when they are censored) (Singer and Willett 2003) and missing data are only a concern if they change of the order of observed outcomes. For these reasons, we use a complete-case approach, which excludes observations with missing values. In addition, we restrict the sample to those individuals who report working at least one day after the start of the observation window, in order to ensure that the job accessibility measures based on daytime locations occur prior to employment. This restriction excludes seven individuals (or five percent of the sample). In analyses not reported here (but available upon request), we assess how this restriction may impact our estimates by including these individuals using a zero-record approach,[5] where the first observation for each individual is duplicated, treated as time zero, and is coded to occur prior to finding work. The estimates produced by this approach are substantially similar to the findings reported here.

[5] This method allows us to include 6 of the 7 censored individuals who reported work on the first day of the study. For one individual, the NSRP data did not include GPS location estimates for the first observed day and the individual was not included in the zero-record approach.

Results

Before describing the regression results, we first discuss the characteristics of the NSRP sample. As Table 1 shows, the average age of the sample is 36 years old, over 90 percent identify as black, and more than one-quarter has not finished high school. Nearly half of the sample is single and the majority are fathers. Importantly, a relatively large percent (16 percent) are living in shelters at reentry. In addition, the vast majority (79 percent) has held a job in the formal labor market prior to the most recent incarceration. Moreover, 78 percent has had a felony conviction prior to incarceration, indicating that the experience of searching for work with a felony is not new.

<Table 1 about here >

We then look at the geographic distribution of job openings in New Jersey. As Figure 1 displays, there are relatively high concentrations of openings in the northeastern regions of New Jersey around Newark and extending approximately 40 miles west and southwest of the city center. This pattern holds when looking at openings for low-skilled jobs only. This concentration in the Newark area appears uniform, however there are large differences between block groups in the top quintile. In the top quintile, the block group with the highest estimated number of openings has twice as many as the block group with the lowest number. Overall, the figure shows large variation in the estimated number of total job openings and low-skilled job openings around Newark, New Jersey.

<Figure 1 about here >

We also examine the daytime locations of the NSRP sample. As Figure 2 shows, our sample of men on parole spend most of their time around Newark and nearby areas; however, individuals do travel outside of the Newark area, particularly in northern New Jersey and some select block groups in the south of the state, if only occasionally. Even if the proportion of time spent in these areas is quite modest, these data suggest that reentering individuals have a broader geographic range of travel than prior reentry scholarship often suggests.

<Figure 2 about here >

The maps emphasize the importance of considering daytime geographic movements and travel for finding work. We test this proposition directly using OLS regression models, which regress the proportion of days working on job accessibility measures for residential block group and daytime locations. As Table 2 describes, residential job accessibility is not associated with the proportion of days working; however, job accessibility based on daytime locations is positively related, where a one standard deviation increase in job accessibility based on daytime locations is associated with a .10 unit increase in the proportion of days worked. Notably, no other covariates are associated with the proportion of days worked, which is generally consistent with prior reentry scholarship that finds few post-release and demographic factors related to employment duration after release from prison (Visher and Kachnowski 2007). The models reported in Table 2 consider measures of work and accessibility aggregated over the entire study period, and they estimate how employment duration over this period is related to job accessibility. As such, the measures of daytime locations reflect time as both unemployed and employed, and the associations estimated from the OLS models could simply reflect the fact that individuals work in areas with higher rates of job accessibility. Given the imprecise timing in this model, our next set of models considers job accessibility prior to first day of work.

<Table 2 about here >

Table 3 reports findings from Cox proportional hazard models, which estimate time to first day of work. As the table shows, we find that residential job accessibility is positively but not significantly associated with time to work. Compared to the residential accessibility estimates, job accessibility measures based on daytime locations have much larger positive associations with time to first day of work. The magnitude and significance of the association remains relatively consistent in models with and without control variables for demographics, post-release characteristics, and pre-incarceration characteristics. For job accessibility based on daytime locations, the hazard ratio of 0.261 indicates that the hazard of employment, or the rate at which individuals find work, is 30 percent higher with each increase in the standard deviation of the accessibility measure.[6] Looking to the other covariates, the estimates suggest that previous criminal justice characteristics are also salient but in offsetting ways, where the number of incarcerations is positively associated with the hazard to first day of work but the number of convictions is negatively related. In addition, we find that no other post release or demographic factors are associated with the hazard to employment.

<Table 3 about here >

Hazard ratios provide insight into the relative benefits of residential and daytime job accessibility for shortening time to work; however, it is not obvious how these ratios translate into survival estimates of remaining unemployed. To better illustrate the role of residential and daytime accessibility for time to work, we plot the findings as survival curves in Figure 3. The figure presents survival curves based on different levels of job accessibility for residential address and daily locations; all other variables are held at their sample means or at their modal values, as in the case of categorical measures such as education attainment and marital status. The "residential" and "daily locations" survival curves are based on one standard deviation increases in the job accessibility measures. The "residential and daily locations" survival curve

[6] The hazard ratio can be converted to a percentage difference in the hazard using the formula: 100*(Exp(coef)-1).

reflects the survival rate of individuals whose job accessibility measures for residence and daily locations are both one standard deviation above the sample mean. This figure illustrates the importance of spending daytime hours in geographic areas with high rates of job openings, as well as the combined value of improving job accessibility based on both residential and daytime locations.

<Figure 3 about here>

The above models estimate time to first job using job accessibility measures based on all job openings within a 50-mile radius, as opposed to considering jobs that are perhaps most relevant to men on parole, or low-skilled, low-income openings that do not require college degrees. In the next set of models, we describe findings for measures that distinguish among these three categories (see Table 4). As with the main findings reported in Table 3, we see positive associations between accessibility and time to first day of work. However, the size of the coefficient on job accessibility based on residential location is slightly larger and is significant for models that consider low-skilled and low-income jobs. For these jobs, the relative importance of residential job accessibility is slightly larger compared to the importance of daytime accessibility, although these differences are not significantly different. For jobs that do not require a college degree, the associations for residential and daytime job accessibility are more similar to the findings that consider all job openings, as reported in Table 3. For these non-college jobs, the association between residential accessibility is positive but non-significant and the association between daytime accessibility is positive (0.268) and significant. In this model, the hazard of employment is 31 percent higher with each increase in the standard deviation in daytime location job accessibility.

<Table 4 about here >

Discussion

This paper used an innovative and novel data set of real-time GPS location estimates to assess the role of job accessibility for finding work among men on parole. Examining daytime locations reveals that our sample of poor, urban, and minority jobseekers are more mobile than the reentry scholarship sometimes assumes and that the places they go during the day matters for their job search and employment outcomes. Specifically, we find that daytime job accessibility measures, and not residential measures, are positively associated with proportion of days worked over the study period. When we examine job accessibility that occurs prior to first day of work, we find that both residential and daytime locations are positively associated with the hazard for time to first job but that job accessibility based on daytime locations is significantly related. Accessibility based on daytime travel is more strongly associated with finding work when we consider all job openings and openings that do not require college degrees. Residential-based job accessibility measures are more consequential when considering jobs that are low-skilled or low-income; however, in all cases, daytime travel remains a relevant factor for predicting time to employment.

The findings emphasize the importance of considering nonresidential locations in spatial mismatch perspectives, and they suggest that daytime mobility is a salient consideration for ameliorating job inaccessibility based on residence. At the same time, however, there are some limitations that must be considered. First, this paper examined the daytime movements of a specific and relatively small sample of men on parole in Newark, New Jersey. We suggest that this population is an appropriate first case study, particularly since these are some of the most disadvantaged jobseekers that are presumably the most negatively impacted by residential spatial mismatch. However, scholarship would benefit from future research using similar methods with more diverse and larger samples and in other metropolitan areas with different transportation and land use characteristics. For example, job accessibility based on daytime travel could be particularly relevant to this group of jobseekers, where jobs and hiring may more dependent on face-to-face interactions (Pager, Western, and Sugie 2009) and geographic travel as opposed to online application processes. Moreover, daytime travel may be more common in areas such as Newark, where there are several public transportation systems, even if these public options are not as extensive as major metropolitan centers. Another limitation is that we cannot fully control for attributes of the men in this study that may influence both their ability to find work and their ability and preference to find housing and search for work in particular areas. Although we include numerous control variables for demographics, post-release and pre-release circumstances, there may be selection bias in where people spend their time (living and searching for work) that affect their success in the job market.

Despite these limitations, the findings extend spatial mismatch perspectives by illustrating the importance of daytime locations in accessibility, and they point to several key recommendations for reentry policy. First, more generally, evidence that spatial mismatch extends to where people spend their time in ways that may trump an individual's residence has important ramifications for where we think low-income households should live. Second, if residential characteristics are less important than daytime mobility for employment prospects, reentry policymakers might focus more on how we can influence where people search for work rather than on where they live, where the latter aim is comparatively more difficult and costly. One way that this could be operationalized for individuals recently released from prison would be to improve transportation access by providing bus or subway fare and information on job clusters. Expanding transportation access and job cluster information, which is often more stable than point-in-time job openings information, are viable approaches for reentry service providers navigating a fiscally constrained context.

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FIGURE 1: Job openings around Newark, New Jersey

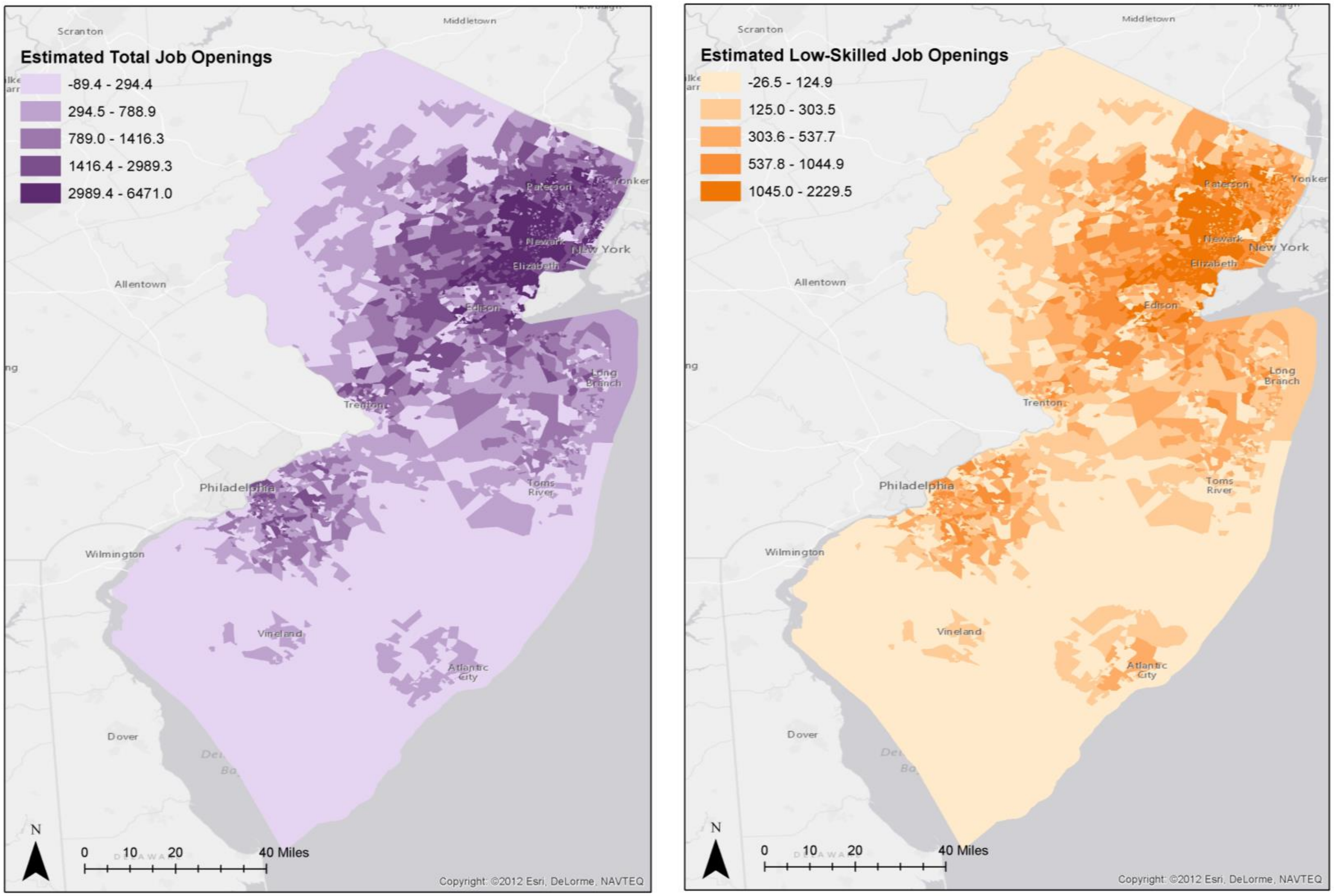


FIGURE 2: Daytime locations of men on parole, New Jersey state and Essex County, New Jersey

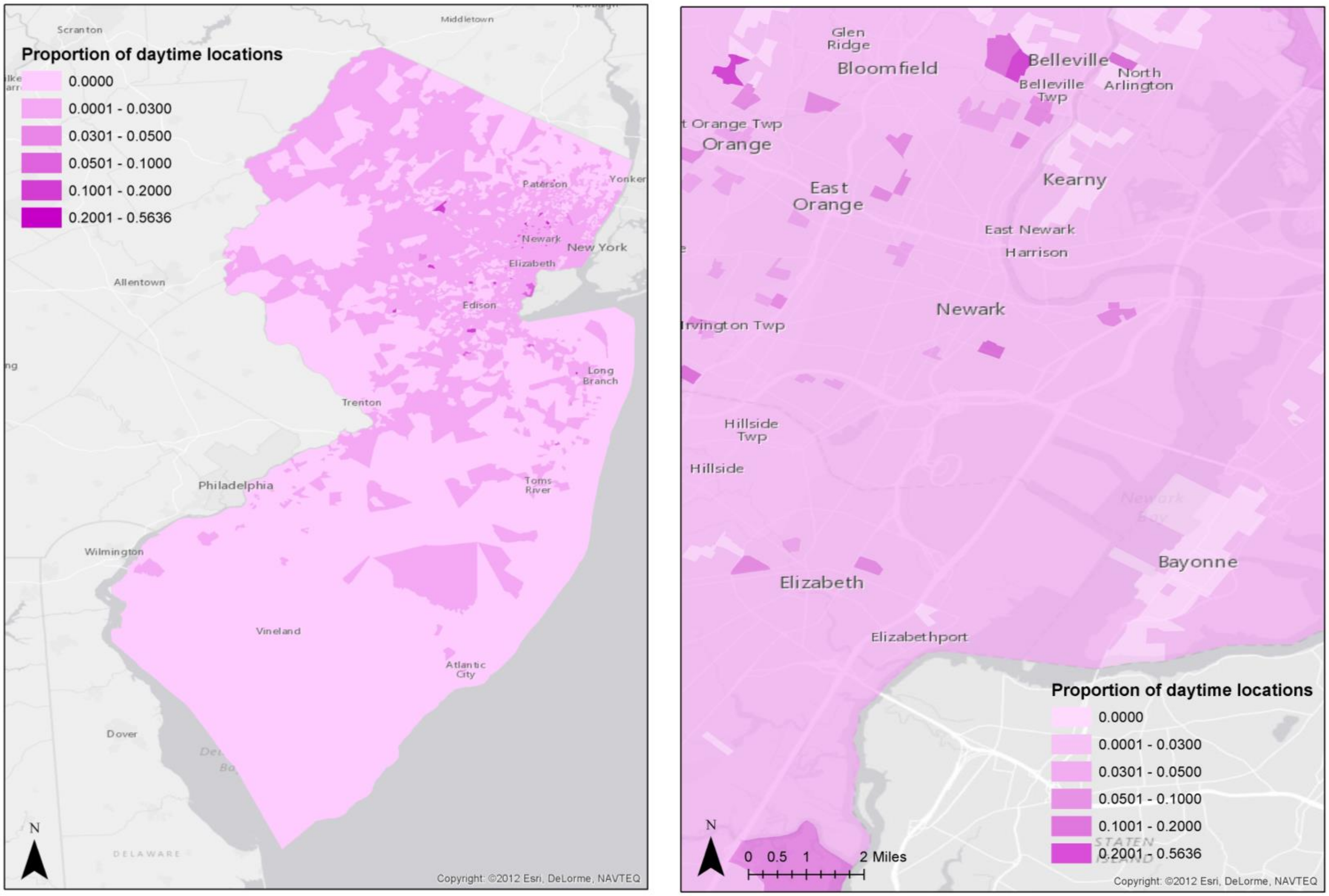
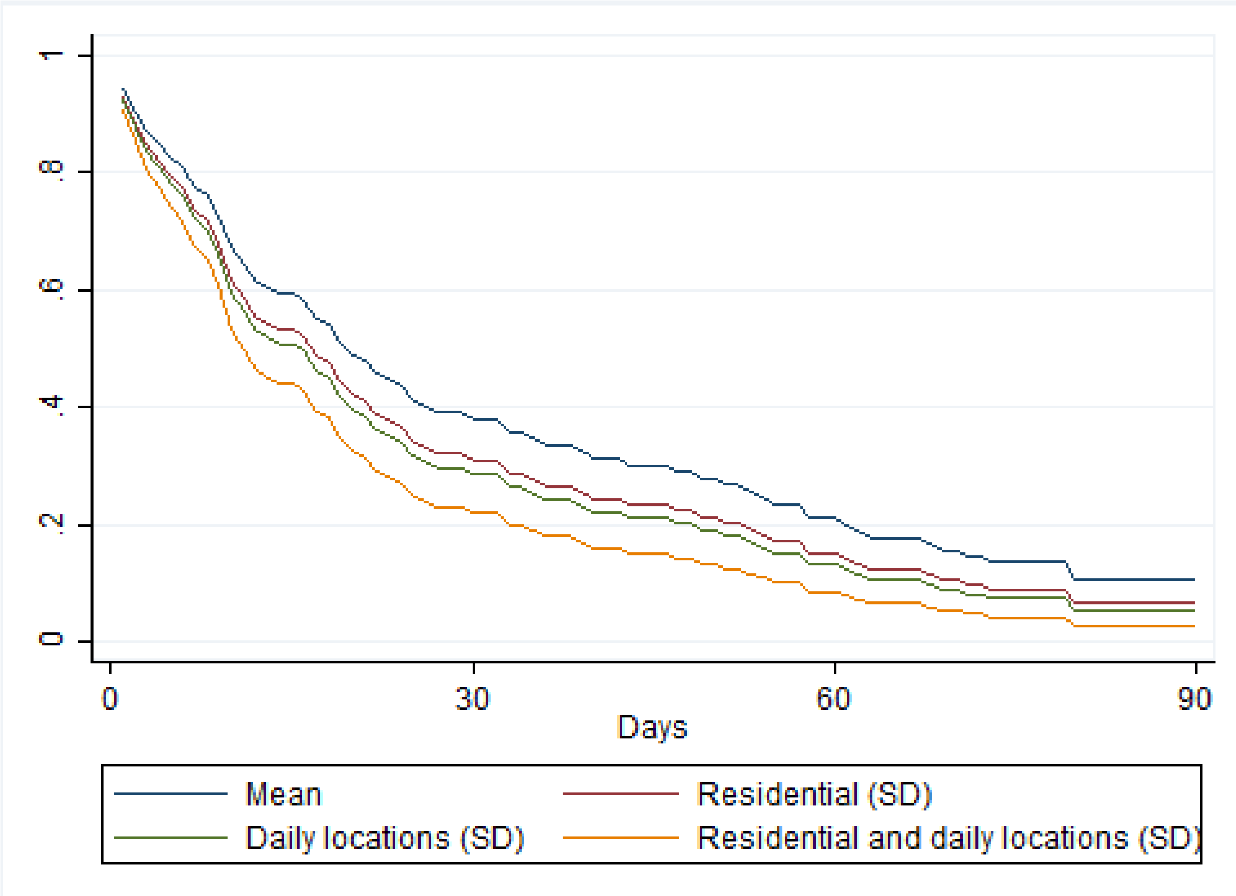


FIGURE 3: Survival curves by job accessibility, holding other factors constant at their means or at their modal value



Notes: "Mean" survival curve is based on job accessibility measures for residential and daily locations at their means and the following sample characteristics: mean age, black, high school graduate/GED, single, one child, mean social support scale, mean self-reported health, mean length of recent incarceration, formal labor market job pre-incarceration, mean age at first incarceration, mean convictions pre-incarceration, one incarceration pre-incarceration, and at least one felony conviction pre-incarceration. "Residential (SD)" curve is based on the above characteristics but the job accessibility measure based on residence is one standard deviation higher than the mean. "Daily locations (SD)" is based on the above characteristics but the job accessibility measure based on GPS estimates is one standard deviation higher than the mean. "Residential and daily locations (SD)" is based on the above, with one standard deviation higher than the mean for accessibility measures based on both residence and daily locations.

TABLE 1: Sample Characteristics

	Mean/%	SD
Age	35.80	10.07
Black	90.32	
Education		
Less than HS	28.24	
HS graduate/GED	45.80	
Some college	23.66	
College	2.29	
Relationship status		
Single	48.09	
Married	5.34	
Partner	46.56	
Total children	1.55	1.47
Social support scale	4.01	1.18
Self-reported health	2.24	1.16
Mental health diagnosis	9.16	
Living in a shelter at reentry	15.27	
Length of recent incarceration	4.22	3.72
Pre-incarceration characteristics		
Any formal labor market job	78.63	
Age at first incarceration	24.10	6.58
Number of convictions	6.01	4.16
Number of incarcerations	0.98	1.19
Any felony conviction	77.86	
N	131	

Notes: job accessibility measures based on residence and daily locations are standardized, where mean=0 and standard deviation=1.

TABLE 2: Proportion of days working

	Residential only			With daytime locations			With controls		
	Coef	SE		Coef	SE		Coef	SE	
Job accessibility									
Residential	0.016	(0.022)		0.008	(0.017)		0.010	(0.021)	
Daytime locations				0.083	(0.022)	***	0.097	(0.021)	***
Age							-0.002	(0.003)	
Black							0.042	(0.068)	
Education (less than HS)									
HS graduate/GED							0.052	(0.052)	
Some college							0.035	(0.054)	
College							-0.019	(0.084)	
Relationship status (single)									
Married							-0.061	(0.064)	
Partner							0.006	(0.042)	
Total children							-0.010	(0.012)	
Social support scale							0.008	(0.015)	
Self-reported health							-0.010	(0.016)	
Mental health diagnosis							-0.075	(0.058)	
Living in a shelter at reentry							-0.085	(0.061)	
Length of recent incarceration							0.001	(0.005)	
Pre-incarceration characteristics									
Any formal labor market job							-0.047	(0.051)	
Age at first incarceration							-0.001	(0.003)	
Number of convictions							0.009	(0.007)	
Number of incarcerations							-0.027	(0.027)	
Any felony conviction							0.043	(0.048)	
Intercept	0.169	(0.019)	***	0.169	(0.017)	***	0.191	(0.130)	
R-squared	0.006			0.154			0.281		
N	131			131			131		
*p<0.05, **p<0.01, **p<0.001									

TABLE 3: Cox proportional hazard models predicting time to first day of work

	Residential			With Daytime Locations				With Controls			
	Coef	Exp(coef)	se(coef)	Coef	Exp(coef)	se(coef)		Coef	Exp(coef)	se(coef)	
Job accessibility											
Residential	0.051	1.052	(0.110)	0.060	1.062	(0.114)		0.192	1.212	(0.119)	
Daytime locations				0.231	1.260	(0.046)	***	0.261	1.298	(0.064)	***
Age								0.005	1.005	(0.020)	
Black								0.549	1.732	(0.544)	
Education (less than HS)											
HS graduate/GED								0.023	1.023	(0.334)	
Some college								0.140	1.150	(0.337)	
College								-1.297	0.273	(1.290)	
Relationship status (single)											
Married								0.272	1.313	(0.507)	
Partner								-0.374	0.688	(0.301)	
Total children								0.049	1.050	(0.088)	
Social support scale								-0.243	0.784	(0.129)	
Self-reported health								0.003	1.003	(0.112)	
Mental health diagnosis								-0.738	0.478	(0.482)	
Living in a shelter at reentry								-0.573	0.564	(0.413)	
Length of recent incarceration								0.021	1.021	(0.034)	
Pre-incarceration characteristics											
Any formal labor market job								-0.296	0.744	(0.306)	
Age at first incarceration								-0.031	0.969	(0.024)	
Number of convictions								0.078	1.081	(0.040)	*
Number of incarcerations								-0.371	0.690	(0.156)	*
Any felony conviction								0.029	1.029	(0.343)	
Person-days		3394			3394				3394		
*p<0.05, **p<0.01, ***p<0.001											

TABLE 4: Cox proportional hazard models predicting time to first day of work, alternate measures of job accessibility

	Low skill				Low income				No college			
	Coef	Exp(coef)	se(coef)		Coef	Exp(coef)	se(coef)		Coef	Exp(coef)	se(coef)	
Job accessibility												
Residential	0.235	1.265	(0.119)	*	0.233	1.262	(0.118)	*	0.202	1.224	(0.122)	
Daytime locations	0.225	1.252	(0.066)	***	0.174	1.190	(0.078)	*	0.268	1.307	(0.058)	***
Age	0.017	1.017	(0.019)		0.002	1.002	(0.021)		0.010	1.010	(0.019)	
Black	0.584	1.793	(0.574)		0.455	1.576	(0.557)		0.599	1.820	(0.549)	
Education (less than HS)												
HS graduate/GED	-0.014	0.986	(0.331)		0.041	1.042	(0.341)		0.002	1.002	(0.330)	
Some college	0.248	1.281	(0.336)		0.358	1.430	(0.331)		0.120	1.127	(0.337)	
College	-1.575	0.207	(1.310)		-1.249	0.287	(1.190)		-1.443	0.236	(1.317)	
Relationship status (single)												
Married	0.287	1.332	(0.516)		0.328	1.388	(0.509)		0.260	1.297	(0.510)	
Partner	-0.268	0.765	(0.301)		-0.347	0.707	(0.303)		-0.341	0.711	(0.295)	
Total children	0.036	1.037	(0.086)		0.046	1.047	(0.087)		0.045	1.046	(0.088)	
Social support scale	-0.236	0.790	(0.126)		-0.197	0.821	(0.126)		-0.252	0.777	(0.130)	
Self-reported health	-0.002	0.998	(0.117)		0.003	1.003	(0.122)		-0.007	0.993	(0.113)	
Mental health diagnosis	-0.558	0.572	(0.486)		-0.772	0.462	(0.518)		-0.675	0.509	(0.479)	
Living in a shelter at reentry	-0.169	0.845	(0.386)		-0.221	0.802	(0.396)		-0.516	0.597	(0.401)	
Length of recent incarceratio	-0.003	0.997	(0.033)		0.001	1.001	(0.032)		0.019	1.019	(0.034)	
Pre-incarceration characteristics												
Any formal labor market job	-0.573	0.564	(0.320)		-0.358	0.699	(0.324)		-0.365	0.694	(0.294)	
Age at first incarceration	-0.029	0.971	(0.023)		-0.026	0.974	(0.024)		-0.030	0.970	(0.023)	
Number of convictions	0.117	1.124	(0.029)	***	0.088	1.092	(0.035)	*	0.089	1.093	(0.036)	*
Number of incarcerations	-0.460	0.631	(0.153)	**	-0.299	0.742	(0.150)	*	-0.418	0.658	(0.155)	**
Any felony conviction	-0.105	0.900	(0.343)		0.069	1.071	(0.349)		-0.031	0.969	(0.339)	
Person-days		3394				3394				3394		
*p<0.05, **p<0.01, ***p<0.001												