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

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Abstract

Individuals recently released from prison confront many barriers to employment. One potential obstacle is *spatial mismatch*—the concentration of low-skilled, nonwhite job-seekers 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 article, 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 spatial mismatch based on residence and daytime locations. Our findings suggest that the ability of low-skilled, poor, and urban individuals to compensate for their residential deficits by traveling to job-rich areas is an overlooked and salient consideration in spatial mismatch perspectives.

Keywords

Spatial mismatch; Reentry; Employment; GPS information

Introduction

More than 600,000 people leave prison in the United States every year (U.S. Department of Justice 2015). Employment outcomes for these individuals are often poor because of various factors related to their pre-incarceration characteristics and reentry circumstances, including limited education and employment experience, occupational restrictions, and criminal record stigma (Holzer et al. 2004; Pager 2007a; Western 2006). Individuals recently released from prison are disproportionately low-income and nonwhite, and they often return to neighborhoods with high rates of poverty and concentrated disadvantage (Harding et al. 2013; Sampson and Loeffler 2010). Over the past decades, these areas have experienced an out-migration of low-skilled jobs and a deterioration of secondary sector work, leaving

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individuals with scarce job opportunities within their residential areas (Crutchfield 2014; Wilson 1996). This study examines the extent to which spatial mismatch (Kain 1968) affects employment for men under parole supervision by the Newark office of the New Jersey Parole Board. We not only analyze spatial mismatch based on residential locations but also use GPS measures collected from smartphones to assess whether daytime locations are associated with employment.

The proposition that where people go during the day affects their likelihood for finding work may appear obvious. However, in practice, knowledge about the location of available jobs is not well known (Ihlanfeldt 1997), and people often learn about opportunities through social networks (Calvó-Armengol and Zenou 2005). Given their crime and incarceration histories, men on parole are thought to have less-effective social networks (Hagan 1993; Sullivan 1989), and reentering individuals may not know where to look for work. Further, extensive search costs are incurred when available jobs are not proximate to residential areas (Stoll 1999), and prior research has suggested that poor individuals often travel to places that are disadvantaged, similar 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.

This study uses real-time smartphone data collected from a sample of men recently released from prison in Newark to extend previous research on spatial mismatch in several ways. First, we describe how residence is an incomplete measure of spatial context, which does not capture the places that individuals frequent and is subject to error given high rates of instability at reentry (Harding et al. 2014). Second, we directly examine employment outcomes using self-reported measures to capture an array of jobs, including off-the-books and temporary positions. These types of jobs are often missed in reentry research that considers formal employment (however, see Western et al. 2015). Third, we construct sophisticated measures of job accessibility for residential and daytime locations and use these measures to examine whether daytime travel ameliorates or exacerbates residential spatial mismatch. This information is a key contribution because the few reentry studies that have examined spatial mismatch have focused exclusively on parolees' residential locations (Bellair and Kowalski 2011; Chamberlain et al. 2014). Finally, we examine how access to automobiles affects the association between spatial job accessibility and employment.

We find that residential spatial mismatch lengthens time to employment, particularly when considering low-skilled and low-income jobs. However, we also find that job accessibility based on daytime locations is important for finding work and is often more consequential than residential accessibility. Our findings highlight the importance of daytime locations, which are often overlooked in spatial mismatch scholarship. We recommend that parole and reentry organizations focus on job clusters, which are fairly stable compared with information on job openings, and find ways to connect men on parole to known clusters by increasing transportation options. More broadly, these findings support the notion that individuals can and do travel outside their residential areas to access resources and that this mobility can compensate for residential deficits. Although we cannot control for the fact that those who are more likely to spend time in job-rich areas may also be more employable, we can say that time spent in those areas appears to pay off for employment.

Spatial Mismatch

Research on spatial mismatch[1] has evaluated 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 Kain (1968) 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 isolated in central cities away from job growth and that this shift was one of the causes of widespread inner-city joblessness. Wilson (1987) later reinforced this notion in his influential book, *The Truly Disadvantaged*.

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 households were less likely to be located near areas of employment growth. Scholars have found consistent evidence for spatial mismatch in areas as diverse as Los Angeles (Blumenberg and Ong 1998; Johnson 2006; Stoll 1999); Washington, DC (Stoll 2006); the San Fransicso Bay Area (Raphael 1998); and Atlanta, Boston, and Detroit (Johnson 2006). This research has found that low-income and minority households generally live farther from employment opportunities than white and higher-income households. In addition, using strong empirical techniques that address selection bias in terms of spatial location and employable attributes, this literature has concluded that spatial proximity matters for employment and earnings.

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 than suburban ones in the Boston metropolitan area. Further, Cervero et al. (2002) found no relationship of regional job accessibility for employment outcomes among welfare recipients in Alameda County, California. Moreover, Sanchez et al. (2004) found no effect from increased transit access on employment outcomes for Temporary Assistance to Needy Families (TANF) participants in a variety of metropolitan areas.

Spatial Mismatch and Reentry From Prison

Spatial mismatch has been considered a primary barrier for finding employment and preventing recidivism at reentry (Morenoff and Harding 2014). Reentering individuals live in some of the most disadvantaged areas, with high rates of unemployment, crime, and poverty (Harding et al. 2013; Sampson and Loeffler 2010). Although employment difficulties for individuals living in these regions are already considered severe, reentering individuals are even more vulnerable to these challenges because of the myriad obstacles to

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

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 job-seekers (Holzer et al. 2007; Pager 2003, 2007b; Pager et al. 2009). Job-seekers with previous convictions and incarcerations may have fewer social connections to work opportunities (Hagan 1993; Sullivan 1989) and limited resources to travel to job openings (Pager 2007b). Even apart from their conviction and imprisonment, reentering individuals typically lack work experience and human capital, and the majority do not have a high school diploma (Raphael 2011).

Little empirical research exists on spatial mismatch for employment at reentry. To our knowledge, only one study has examined the role of local labor market conditions on individual employment after release from prison: Sabol (2007) found that local unemployment rates were negatively associated with time to employment. The study is an important contribution to reentry scholarship given that scholars have sometimes suggested 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 Raphael and Weiman 2007; Sabol 2007). At the same time, however, Sabol used broad measures of 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 limitations, particularly in the reentry realm, because 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 examining local labor markets and criminal offending has suggested that spatial mismatch has implications for recidivism. In these studies, employment is not directly measured but is considered the main mechanism mediating labor markets and recidivism. In a study of individuals on parole in California, Raphael and Weiman (2007) found that local unemployment rates were positively associated with return to custody, particularly for individuals with a lower risk of violations. Other work by Wang et al. (2010) found that local unemployment rates were associated with violent offending and that these relationships differed by race and industry. Although the aforementioned studies considered unemployment rates as measures of job accessibility, a recent study of individuals on parole in Ohio used more precise measures of local job access to examine recidivism rates (Chamberlain et al. 2014). In contrast to previous scholarship, these researchers found that greater job access is related to higher rates of recidivism. Although their measures of job accessibility are more complex than unemployment rates and consider distances to jobs and per capita factors, these measures have limitations that may explain the unexpected findings. Specifically, they 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 using such parameters can have large ramifications, particularly in disadvantaged urban areas with higher concentrations of businesses and lower proportions of labor force participants.

Throughout all this research, spatial mismatch and local labor markets are theorized at the residential level, with little regard to geographic mobility and nonresidential labor markets. Although residential place is undoubtedly an important context, it does not necessarily correspond to where people spend most of their time (Basta et al. 2010). Indeed, residential neighborhood is only one of the numerous locations encountered by individuals throughout their daily routines (Jones and Pebley 2014; Krivo et al. 2013; Leverentz 2016; Matthews and Yang 2013; Palmer et al. 2013). We propose that the amount of time that people spend in job-rich areas likely affects their ability to find work. Individuals may learn about job openings from businesses that they frequent, friends or family who live more proximate to commercial areas, or local service providers. Individuals may also actively seek out areas with better employment opportunities to compensate for their residential disadvantages. Although we do not discount the importance of residential location, we suggest that the focus on residence excludes the range of contexts that individuals inhabit throughout the day.

Outside of the reentry context, prior research on where people search for work and how search methods affect employment has found that low-income and minority job-seekers travel farther to search for work (Holzer et al. 1994; Stoll 1999). How people travel in their search depends on the labor market characteristics of their residential areas and their own travel costs: people with higher travel costs (and lower ability to pay) and those who are reliant on public transportation do not travel as far as those with lower costs and access to cars (Blumenberg and Manville 2004; Holzer et al. 1994; Raphael and Rice 2002; Stoll 1999; Stoll and Raphael 2000). For men recently released from prison who live in neighborhoods that lack job opportunities, access to automobiles may improve employment outcomes in at least three ways. First, car access may make job searches more efficient and lead more quickly to employment. Second, car access may reduce the importance of residential job accessibility for finding employment by decreasing the costs of leaving residential areas. Third, car access may increase the importance of spending time in job-rich areas. Having access to a car may make it easier for people to capitalize on job information and potential opportunities in distal areas. We examine these three possibilities in our analysis.

Daytime Locations in Prior Scholarship

The importance of daytime locations, as well as their measurement, is increasingly highlighted in research on “activity spaces”—the locations that individuals encounter in the course of their daily routines (see Matthews and Yang 2013 for a recent review). Activity spaces shape outcomes, such as health (Matthews and Yang 2013), youth development (Browning and Soller 2014), and subjective well-being (Palmer et al. 2013). In this article, we suggest that daytime locations may also structure employment outcomes. Although activity spaces can be described at a granular level (e.g., Kwan 2000), research has often measured these locations using geographic information system (GIS) data from social surveys. These data consider key destinations that individuals routinely visit, such as their primary grocery store, health care provider, and place of worship (Jones and Pebley 2014; Krivo et al. 2013).

Although these measures are some of the few that capture daytime locations, they are limited in several ways. Most obviously, they fail to measure locations that do not correspond to predetermined activity-based categories. Time spent away from home for leisure activities or visiting friends may expose people to social networks, resources, and information in ways that are more consequential than frequenting grocery stores or health care providers. A second limitation is that they do not measure the amount of time—or the "contextual dosage"—that people spend in these locales (Browning and Soller 2014). Measures based on time diaries can address these issues, but they encounter other measurement concerns, such as retrospective reporting bias and respondent error (Stone et al. 2007).

To address these issues, researchers have recently suggested using global positioning system (GPS) data on geographic locations to measure activity spaces (Browning and Soller 2014; Palmer et al. 2013). Using this approach, smartphone applications passively collect GPS information at specific time intervals while individuals go about their daily routines. Drawing from *experience sampling methods*—systematic sampling of everyday experiences (Csikszentmihalyi and Larson 1987)—researchers consider frequently collected GPS information as measures of contextual exposure. We follow this approach for the location data. In addition, we use self-reports of daily employment, which are gathered from smartphone surveys, to measure employment at the person-day level. Collected in real time, these measures capture irregular or unstable experiences (Stone et al. 2007), such as employment at reentry. They also measure any type of work for pay, including off-the-books and temporary jobs, which are most relevant to people recently released from prison. This approach improves on most previous reentry employment research, which has often focused on jobs in the formal sector and those covered by unemployment insurance (Apel and Sweeten 2010; Pettit and Lyons 2007; Sabol 2007; Visher et al. 2010; for an exception, see Western et al. 2015).

Data, Methods, and Measures

In addition to using real-time GPS location and daily employment information, this study 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 on parole in Newark, New Jersey. NSRP participants were sampled from a complete census of all eligible parolees recently released from prison to the Newark parole office between April 2012 and April 2013. Individuals were eligible to participate if they were male, searching for work, and neither gang-identified nor recently convicted of a sex offense. Eighty-nine percent of the 152 individuals contacted (or $N = 135$) agreed to participate in the study. Our final sample is 131 because we excluded four individuals who 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 finds no significant differences (Sugie 2016). The setting of Newark, which is a particularly disadvantaged urban center, is an important context. In 2012, the city's unemployment rate was 13.8 %, compared with 9.4 % for New Jersey and 8.1 % for the country. For men on parole in this urban area, jobs were particularly hard to obtain. We suggest that the NSRP sample may be most similar to men on parole in particularly disadvantaged urban areas, as opposed to other geographic settings, which is an appropriate scope condition given the spatial concentration of imprisonment (Harding et al. 2013; Sampson and Loeffler 2010).

NSRP participants completed an initial interview, received smartphones with a data-collection application (app), and were followed for three months through the phones. The smartphone app passively collected GPS information every 15 minutes during daytime hours (8 a.m. to 6 p.m.), producing voluminous and precise location data. Location estimates were collected 87 % of the expected time. Approximately 6 % 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 % of location estimates were not collected because participants had turned off the function on their NSRP smartphone application. Examining these periods revealed no apparent patterns by day of the week or time of the day (Sugie 2016). For this article, we consider location estimates within New Jersey. Our final analysis sample includes a large and detailed data set of 354,691 passively observed GPS location estimates, which refer to 2,508 census block groups (or 40 % of all New Jersey block groups).

Methods

We first examine the locations of job openings and the daytime locations of the sample. This fine-grained descriptive detail is important because 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 accessibility, and employment; we conduct two-tailed significance tests across all models.[2] First, we examine how residential and daytime job accessibility are associated with the number of days employed. We estimate ordinary least squares (OLS) regression models in which the outcome is the proportion of days employed during the study period.[3] 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 during the study period, the estimates reflect accessibility both prior to and after finding employment. Because 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 daytime job accessibility are related to time to employment.[4] We use a Cox

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[2]We use two-tailed tests, as opposed to one-tailed tests, because it is plausible that the associations between job accessibility and employment could run in a negative direction, where spending time in job-rich places is associated with unemployment. For example, individuals could spend time at bars or other undesirable locations in close proximity to jobs that they are not actively trying to obtain.

[3]We conducted two tests to check for heteroskedasticity of residuals: a plot of residuals versus predicted values and Cameron and Trivedi’s decomposition of IM-test. Both indicate that heteroskedasticity is not a concern.

[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 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. This rate is lower than rates of recidivism to prison estimated by the U.S. Bureau of Justice Statistics in 2005 (3 % versus 8 %, see Durose et al. 2014). Given the relatively low risk of recidivating during the study period, we use the single-decrement approach.

proportional hazards approach to estimate survival models with residential and daytime accessibility (Cox 1975; Singer and Willet 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. We take advantage of the detailed, person-day information on employment, daytime locations, and job accessibility to estimate time to first day of employment. As a nonparametric model, the approach does not require *a priori* modeling assumptions of the functional form of the hazard. To handle *ties*—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 Willet 2003). We use robust standard errors to account for person-day measures correlated within individuals.

Although the fine-grained smartphone information provides a novel test of spatial mismatch at reentry, smartphone data are often characterized by higher rates of missing information for any particular day (Walls and Schafer 2005). We have relatively good data coverage, but 16 % of person-days are missing employment information. In Cox 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 Willet 2003), and missing data are a concern only if they change 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 reported working at least one day after the start of the observation window to ensure that the job-accessibility measures based on daytime locations occur prior to employment. This restriction excludes seven individuals (or 5 % of the sample) and corresponds to 3,394 person-days that occur prior to first day of work (i.e., time at risk). 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] in which the first observation for each individual is duplicated, treated as time 0, and coded to occur prior to finding work. The estimates with this approach are substantially similar to the findings reported here.

In the third part of our analysis, we examine whether having access to a car affects the findings from the Cox models. First, we include car access (in which the respondent either owns a car or has access to one to look for work) as an explanatory variable, which tests whether car access changes time to employment. Second, we add an interaction term with car access and residential job accessibility to examine whether car access changes the importance of residential location for employment. Third, we include an interaction with car access and job accessibility based on daytime locations to test whether access affects the importance of daytime accessibility for employment.

[5]We include six of the seven censored individuals who reported work on the first day of the study. For the seventh individual, the NSRP data did not include GPS estimates for the first observed day.

Measures

Employment

We consider two measures of employment, which are created using real-time, self-reported smartphone survey answers. The first measure is the proportion of days worked of the total number of observed days. The second measure is the number of days until the first day of work, for use in survival models.

These person-day employment measures are based on answers from two smartphone surveys that were sent to participants daily. The first survey was sent to participants' phones at a random time between the hours of 9 a.m. and 6 p.m. and asked about activities that were occurring at that moment. The second was sent to participants at 7 p.m. and solicited information about events and activities throughout the day. If a participant reported working on either of these surveys, he is coded as employed. As noted earlier, we are missing information on 16 % of total person days.

Employment Accessibility

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

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 estimate openings in 2011 using the total number of jobs that are currently occupied in 2011 and the growth rate in jobs from 2009 to 2011. Following Shen (1998, 2001), we assume a turnover rate of 3 %, multiply that by the number of total jobs to produce $O_{jt}(T)$ (the number of job openings due to turnover), and then add that number to job openings from growth ($O_{jt}(G)$), using the growth rate from 2009 to 2011:

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

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):

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

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).[6]

Finally, we adjust these estimates to take into account the fact that job-seekers 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 Eq. (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 that parolees are likely to be concentrated in 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 (i.e., the employed and those seeking work).

Using this approach, we consider two measures of job accessibility. The first is the measure of job openings that accounts for distance and competition, as described earlier. This measure of job accessibility 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 nonweighted measure (O_{jt} in Eq. (1)) with GPS data on daytime locations 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 Eq. (2) because we are interested in the density of available 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 daytime job accessibility throughout the models. Our main models consider all jobs openings; however, it is likely that men on parole seek 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, the measures are standardized, such that the sample mean is 0 and the standard deviation is 1.

Car Access

This measure is dichotomous, with 1 indicating that the participant owns a car or has access to a friend or family member's car to look for work. The question about ownership or access to a car was asked in the initial interview at the beginning of the study.

Other Characteristics

We include a rich array of demographic, reentry, and pre-incarceration characteristics. Demographic and reentry information include age, race, educational attainment, relationship status, number of children, self-reported health, length of most recent incarceration, and shelter residence at reentry.[7] We also include a scale of perceived social support, which is

[6]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, we 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 who work 5 miles away, 30 minutes corresponds to 10 miles, and so forth. Thus, we arrived at a decay parameter of $-0.058 \times 3 = -0.174$, where 0 miles = 1; three miles = .59; five miles = .42; 15 miles = .07; 30 miles = .005; and 50 miles = .0002. Only jobs within 50 miles are included.

based on the Fragile Families and Child Wellbeing Survey and is the sum of the following five responses: *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?* The measure ranges from 1 to 5, with higher values indicating greater perceived social support (α = .67).

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, number of previous incarcerations, and any felony conviction prior to the instant offense.[8] The criminal justice measures come from administrative records from the New Jersey Parole Board and refer to events that occurred in New Jersey. The other information comes from the initial interview.

Results

We first describe the characteristics of the NSRP sample. As Table 1 shows, approximately one-third (32 %) of individuals either own a car or have access to one to look for work. The average age is 36 years old, more than 90 % self-identify as black, and more than one-quarter have not finished high school. Nearly one-half of the sample is single, and the majority are fathers. Importantly, a relatively large percentage (16 %) live in shelters at reentry. In addition, the vast majority (79 %) held a job in the formal labor market prior to the most recent incarceration. Moreover, 78 % had a felony conviction prior to the most recent incarceration, indicating that the experience of searching for work with a felony is not new.

Figure 1 shows the spatial distribution of job openings in New Jersey. The figure shows relatively high concentrations of openings in the northeastern regions of New Jersey near 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, large differences are evident 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 2 shows the daytime locations of the NSRP sample. Individuals spend most of their time around Newark and nearby areas; however, they occasionally travel outside the Newark area, particularly in northern New Jersey and some select block groups in the south of the state. 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 previous studies of reentry scholarship have often suggested.

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

[8] Although these measures describe prior criminal justice contact, tests suggest that multicollinearity is not an issue. Thus, we include these measures as separate variables in the regression models.

The maps emphasize the potential importance of considering daytime locations for finding work. We test this proposition directly using OLS regression models, which regress the proportion of days worked on job accessibility measures for residential block group and daytime locations. As shown in Table 2, residential job accessibility is not associated with the proportion of days worked; however, job accessibility based on daytime locations is positively related, where a 1 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 employment, which is generally consistent with prior reentry scholarship finding few post-release factors related to employment duration after release from prison (Visher and Kachnowski 2007). It is possible that the null findings are related to the relatively short period considered in this project and in prior work, and perhaps post-release circumstances would have greater influence among individuals that have been released from prison for longer amounts of time (Visher and Kachnowski 2007). However, if that is the case, it is all the more notable that daytime job accessibility is strongly associated with employment duration.

The models reported in Table 2 consider measures of work and accessibility aggregated over the study period. As such, the measures of daytime locations are based on 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 job accessibility. Given the imprecise timing in this model, our next set of models considers job accessibility prior to first day of work. Table 3 reports findings from Cox proportional hazard models, which estimate time to first day of work. The table shows that residential job accessibility is positively but not significantly associated with time to employment. Compared with residential accessibility, job accessibility based on day-time locations has a larger positive association 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 demographic, post-release, and pre-incarceration characteristics. For job accessibility based on daytime locations, the hazard ratio of 1.298 indicates that the *hazard of employment*—the rate at which individuals find work—is 30 % higher with each increase in the standard deviation of the accessibility measure.[9] Coefficients on other covariates suggest that previous criminal justice characteristics are also salient but in offsetting ways: the number of incarcerations is negatively associated with the hazard to first day of work, but the number of convictions is positively related. Although speculative, one potential explanation for these associations is that individuals with numerous previous convictions are convicted of less-serious offenses or become increasingly knowledgeable about which employers might be less concerned about convictions. On the other hand, those with previous incarcerations have been convicted of more serious offenses, which may make it more difficult to find work. They also may be dealing with more stressors or negative experiences accumulated from prior incarcerations, which may disadvantage them in the labor market and prolong their search for work. In addition to these findings, the models suggest that no other post-release or demographic factors are associated with the hazard to employment.

[9]The hazard ratio can be converted to a percentage difference in the hazard using the following formula: 100 × (exp(coef.) − 1).

Hazard ratios provide insight into the relative benefits of residential and daytime job accessibility for shortening time to work, but how these ratios translate into estimates of remaining unemployed over time is not obvious. To better illustrate the role of residential and daytime accessibility for time to work, we plot the findings as survival curves. Figure 3 presents survival curves based on different levels of job accessibility for residential and daytime locations; all other variables are held at their sample means or at their modal values (for categorical variables). The "residential" and "daytime locations" survival curves are based on 1 standard deviation increases in the job accessibility measures. The "residential and daytime locations" survival curve reflects the survival rate of individuals whose job accessibility measures for residence and daytime locations are both 1 standard deviation above the sample mean. This figure illustrates the importance of spending daytime hours in job-rich areas as well as the combined value of both living in and spending time in job-rich places.

The preceding models estimate time to first job using 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. In the next set of models, we describe findings for measures that distinguish among those jobs that are low-skilled and low-income and those that do not require college degrees.[10] As with the main findings reported in Table 3, Table 4 shows positive associations between accessibility and time to first day of work. However, the size of the coefficient on residential job accessibility is slightly larger and significant for models that consider low-skilled and low-income jobs. For these jobs, the relative importance of residential accessibility is slightly larger compared with 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. For these noncollege jobs, the association between residential accessibility is positive but nonsignificant, and the association between daytime accessibility is positive (0.268) and significant. In this model, the hazard of employment is 31 % higher with each increase in the standard deviation in daytime accessibility. Although the results regarding daytime accessibility are quite consistent across job types, the differences related to residential accessibility may be due to the residential locations of the sample. For men recently released from prison, it may be easier to obtain affordable residence near low-skilled and low-income jobs, as opposed to the broader pool of jobs. These findings indicate that future research on spatial mismatch should take into account job types that are most relevant for the population of interest.

In the final part of the analysis, we examine how car access affects job accessibility and employment. The Cox models include the full set of control variables; however, Table 5 displays results for only the variables of interest. As Model a shows, access to a car has a modest negative and nonsignificant association with time to employment. Although this result might seem unexpected, the lack of a direct association is consistent with prior

[10]We define low-skilled jobs as those in the following North American Industry Classification System sectors: 11 (agriculture), 23 (construction), 31–33 (manufacturing), 44–45 (retail), 56 (administrative and support and waste management), 72 (accommodation and food services), and 81 (other services). Low-income jobs are restricted to the lowest income category reported in Census LEHD files: $1,250 per month or less. Jobs without a college degree are those in which the LEHD files reports that the incumbent employee does not have a college degree.

research on spatial mismatch among black and white job-seekers (Stoll 1999; Stoll and Raphael 2000). As Model b displays, the interaction term of car access and residential accessibility is modestly positive and nonsignificant, indicating that access to a car does not measurably change the main association between residential accessibility and time to employment. In contrast to these models, access to a car does moderate the association between daytime accessibility and time to employment. In Model c, the interaction is associated with a hazard ratio of 1.367, which indicates that the rate at which individuals with car access find employment is 37 % higher compared with those without access, with each increase in the standard deviation of the accessibility measure. For those without car access, the association between daytime accessibility and employment is slightly reduced but still positive and significant (1.194, *p* value = .007). Therefore, spending time in job-rich areas quickens time to employment for all individuals but particularly for those with access to cars.

Discussion

This study draws on spatial mismatch and prisoner reentry scholarship to examine the role of daytime mobility for employment among men on parole. Whereas the majority of reentry research has focused on residential location, we use novel GPS data, combined with sophisticated measures of job accessibility, to examine both daytime and residential locations of men recently released from prison. We find that individuals in this sample of poor, urban, and minority job-seekers often spend time away from their residential areas. Importantly, the places they go during the day matter for their employment outcomes, where job accessibility based on daytime locations is positively associated with employment duration. When we examine job accessibility prior to the 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 daytime accessibility is significantly related. Accessibility based on daytime locations is more strongly associated with finding work when we consider all job openings and openings that do not require college degrees. Residential accessibility is important among jobs that are low-skilled or low-income, which are most relevant to men recently released from prison; however, for all job types, daytime accessibility remains salient for predicting time to employment. Finally, access to an automobile does not have a direct association with employment; however, car access moderates the association between daytime accessibility and work, where daytime accessibility is more strongly associated with employment among those with access to automobiles. We suggest that car access might facilitate employment by making it easier for people to convert potential work opportunities into jobs.

The findings emphasize the importance of daytime locations in spatial mismatch theory, and they suggest that daytime contexts may compensate for residential deficits among highly disadvantaged groups, such as men on parole. These are salient contributions to both theory and research, which often focus on isolation due to residential location. Although this article examines the role of daytime locations for employment, future research would benefit from considering how daytime travel affects other outcomes that are structured by geographic contexts, as the activity space literature emphasizes. This article uses passively observed GPS estimates to measure daytime locations, and we suggest that this approach will be increasingly common as smartphone data collection becomes ubiquitous in the social sciences. However, similar methods of measuring daytime travel can be used with nonsmartphone approaches, such as time diaries or self-reports using maps (Basta et al. 2010).

Alongside these contributions, however, some limitations must be considered. Mainly, this article examines the daytime movements of a specific sample of men on parole supervision in Newark, New Jersey. Despite the high participation rate (89 %), study participants may be more motivated to find employment compared with those who declined to participate and those who could not be contacted about the study by their parole officers. Several additional factors related to the sample may make residential accessibility less relevant to this group. First, Newark is a disadvantaged urban area, and our sample of job-seekers lived in places with few job opportunities. Perhaps those who live in areas with better job accessibility would benefit more from their residential locations.[11] Second, job accessibility based on daytime travel might be particularly relevant to reentry, where face-to-face interactions are important for employment (Pager et al. 2009). We suggest that in-person contact might be similarly consequential for other less-skilled job-seekers, but daytime locations may be less important for higher-skilled groups. Third, Newark is an urban area with several public transportation systems. Residential location may be more salient in places with fewer transportation options or in areas with more geographical dispersion. Despite the specific nature of the sample, however, we believe the findings are important, particularly because men on parole are some of the most disadvantaged job-seekers and are presumably the most negatively impacted by residential spatial mismatch.

Another main 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 and for post-release and pre-release circumstances, there may be selection bias in where people spend their time (living and searching for work) that affects their success in the job market.

Not with standing 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, our article finds that spatial mismatch extends to where people spend their time in ways that may trump their residence. If residential characteristics are less important than daytime mobility for employment prospects, reentry policy-makers might focus on how we can influence where people search for work rather than where they live. Although this recommendation seems to contrast with recent reentry research calling for changes in residential location (Kirk 2009), our findings align with that study's more general emphasis on the benefits of spending time in nonresidential areas.[12] Compared with changing residential place, encouraging people to

[11]We examined whether residential job accessibility moderated the association between daytime accessibility and employment. We found a negative (but nonsignificant) relationship with the interaction, providing circumscribed evidence that daytime locations may be less important among job-seekers who live in job-rich areas.

[12]Kirk (2009) found that changes in residential location pre- and post-incarceration (as the result of Hurricane Katrina) are related to lower recidivism rates, which he attributed to changes in criminogenic peer influences and routine activities.

spend time in job-rich areas would be more feasible and less costly. One way that this could be operationalized for individuals recently released from prison would be to balance supervision requirements and mobility restrictions with the perceived benefits of daytime travel. Although location restrictions and parole meetings are designed to protect individuals from criminogenic environments (Blumstein and Beck 2005), these constraints may be exacerbating geographic isolation. Reentry service providers might encourage travel to job-rich areas by offering information on job clusters, or areas with large concentrations of employers, which are often more stable than point-in-time information on job openings. Moreover, because car access is helpful for finding work when combined with higher daytime accessibility, transportation access could be improved for others by providing bus or subway fare. Expanding transportation access and offering job cluster information are viable approaches for reentry service providers navigating a fiscally constrained context.

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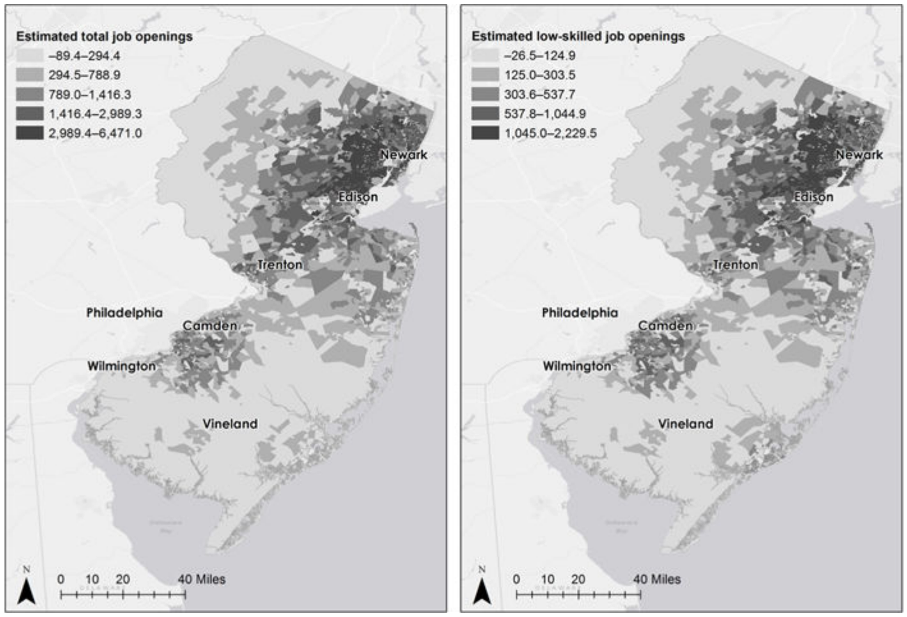

Fig. 1.
Job openings around Newark, New Jersey

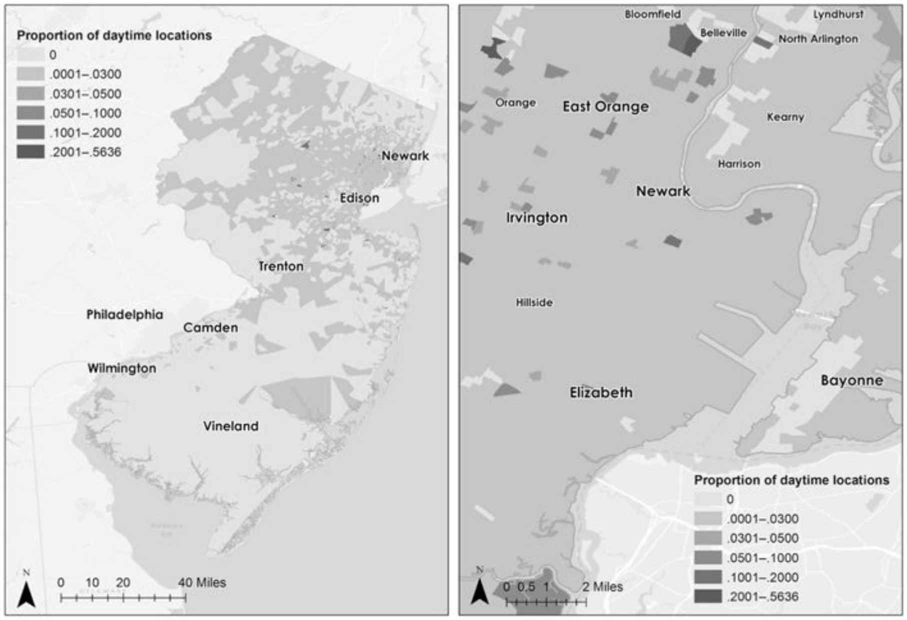

Fig. 2.

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

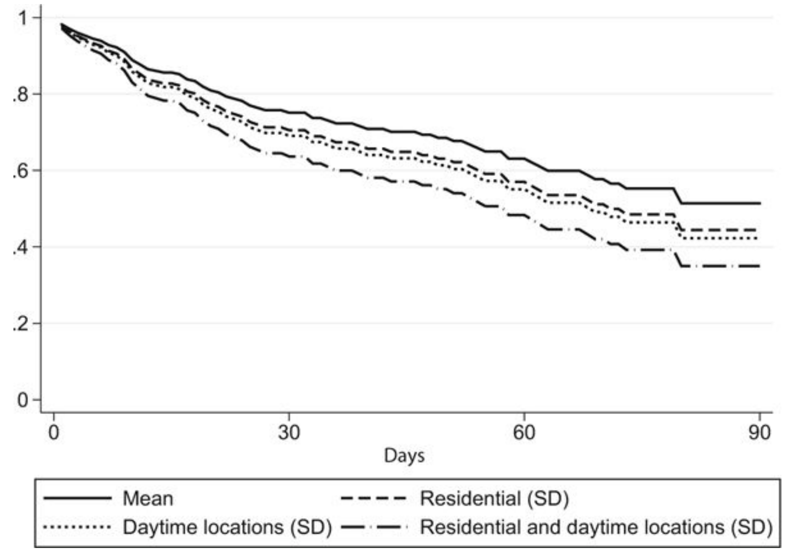

Fig. 3.
Survival curves by job accessibility, holding other factors constant at their means or at their modal value. “Mean” survival curve is based on job accessibility measures for residential and daytime locations at their means and the following sample characteristics: mean age, black, high school 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. “Daytime 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 daytime locations (SD)” is based on the above, with one standard deviation higher than the mean for accessibility measures based on both residence and daytime locations

Table 1

Sample characteristics

	Mean or %	**SD**
Time to First Day of Work (days)	22.20	18.60
Car Access	32.06	
Age	35.80	10.07
Black	90.84	
Education		
Less than high school	28.24	
High school 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	

Table 2

Proportion of days working

	Residential		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 (ref. = less than high school)						
High school graduate/GED					0.052	0.052
Some college					0.035	.054
College					−0.019	0.084
Relationship Status (ref. = 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	.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^2	.006		.154		.281	
N	131		131		131	

*** $p < .001$

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 (ref. = less than high school)									
High school 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 (ref. = 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
N	124			124			124		

Note: The models consider N = 124 individuals and N = 3,394 person-days at risk and under observation prior to first day of work.

* $p < .05$;

*** $p < .001$

Table 4

Cox proportional hazard models predicting time to first day of work, low-skilled, low-income, and jobs requiring no college degree

	Low Skilled			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 (ref. = less than high school)									
High school 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 (ref. = 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 Incarceration	−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
N	124			124			124		

Note: The models consider N = 124 individuals and N = 3,394 person-days at risk and under observation prior to first day of work.

* $p < .05$;

** $p < .01$;

*** $p < .001$

Table 5

Cox proportional hazard models predicting time to first day of work, with car access

	Model a			Model b			Model c		
	Coef.	exp(coef.)	SE (coef.)	Coef.	exp(coef.)	SE (coef.)	Coef.	exp(coef.)	SE (coef.)
Job Accessibility									
Residential	0.190	1.210	0.119	0.169	1.184	0.121	0.245	1.277	0.138
Daytime locations	0.261***	1.298	0.064	0.263***	1.300	0.065	0.177**	1.194	0.065
Car Access	−0.063	0.939	0.296	−0.074	0.929	0.306	−0.165	0.848	0.312
Car Access × Job Accessibility: Residential				0.096	1.101	0.305			
Car Access × Job Accessibility: Daytime Locations							0.312*	1.367	0.148
N	124			124			124		

Note: The models consider $N = 124$ individuals and $N = 3,394$ person-days at risk and under observation prior to first day of work.

* $p < .05$;

** $p < .01$;

*** $p < .001$