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Off to Market: Neighborhood and Individual Employment Barriers for Women in 21st Century American Cities[1]

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Abstract

This paper endeavors to create a better understanding of the barriers to employment faced by disadvantaged urban women in the post-welfare reform era. Using data from the Project on Devolution and Urban Change, a unique geographically-linked, longitudinal, multi-city set of survey data, logistic regression models weigh the relative importance of individual barriers to employment (poor health, childcare and family responsibilities, etc.) and contextual or neighborhood barriers to employment (poverty rate, joblessness rate, etc.) on labor market outcomes. Results reveal that several neighborhood characteristics are predictive of employment, including automobile access, female-headedness, vacancy, and disorder. Results suggest a more complex, nuanced interplay between neighborhood-level variables and individually-measured variables in preventing some women from obtaining both modestly paying employment with few allocated hours of work per week, and also better-paying jobs with more hours of work per week.

Keywords: Neighborhood effects, Welfare reform, Employment, Gender

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Introduction

The Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 fundamentally altered the means by which disadvantaged urban women could live and work. As its name suggests, the act assumed that many single mothers who participated in public assistance programs needed to take personal responsibility for pulling themselves up by their bootstraps. At the same time, it assumed that work opportunities were plentiful enough to allow this personal responsibility to unfold, despite all evidence to the contrary. The act's proponents assumed that work was readily available and that sustained employment would lead out of poverty. Most notably, PRWORA replaced AFDC with Temporary Assistance to Needy Families (TANF), the U.S.'s current welfare transfer program. The policy change instituted punitive sanctioning policies, time limits, and diversion programs aimed at discouraging initial application for TANF or Food Stamps and forced each state to place an annually accelerating percentage of its caseload in work-related activities (Haskins and Blank 2001:12; Moffitt 2002).

Even before welfare reform, employment was equated with economic self-sufficiency and public opinion held that contact with the labor market would increase skills and augment self-esteem (Harris 1993:320). In fact, the Work First programs adopted under PRWORA use a labor force attachment model that assumes that the skills garnered through labor market experience produce advancement, and that this direct experience, rather than education or vocational training programs, is the best way to move former recipients up the job ladder (Corcoran et al. 2000). The logic of welfare reform was therefore "get a job, get a better job, get a career" (Gais et al. 2001:46).

Though the research on welfare reform could probably fill most academics' offices several times over, most existing research misses the reality that women who were forced off of

TANF since 1996 are emplaced. That is, they live in particular neighborhoods that provide networks of neighbors, access to transportation, readily available employment opportunities—or in some cases, none of these things. Therefore, the ability of women to obtain quality employment and upward mobility should depend heavily upon the neighborhoods in which they reside. Though a great deal has been written about the barriers to employment that women who were forced off of TANF face in securing employment, somewhat less research weighs these individual barriers (health problems, childcare and family responsibilities, transportation access, domestic violence, lack of human capital in the form of skills, education, or work experience, etc.) alongside spatial and geographic barriers. The following analyses begin to fill that gap, by asking three main questions: 1) How do neighborhood conditions affect women's employment outcomes, net of individually-measured controls? 2) Which particular neighborhood conditions matter for employment? 3) How do these neighborhood effects operate through time?

Literature Review

The existing literature divides barriers to employment into two main categories, spatial (or contextual) barriers and individual barriers. Due to the complex relationships between individuals and their environments, this is normally not meant to suggest that "individual" barriers arise out of agency or free choice, whereas contextual barriers are structurally driven. Rather, it normally refers to the level of measurement of the data at hand. Individual barriers refer to factors such as health or childcare responsibilities that researchers learn about by asking questions of individuals; spatial or contextual barriers are those that are measured through census data or other aggregate data collected on an urban environment (such as a neighborhood's poverty rate or racial composition). Despite this distinction, there is indeed overlap and interplay between the two, and the present study accounts for both types of employment barriers. The following sections review recent literature on these two types of barriers.

Neighborhood and Spatial Barriers to Employment

Despite some contradictory evidence regarding labor market outcomes, a general consensus is emerging that neighborhood conditions do affect many lifecourse events (South and Crowder 1999). This effect depends heavily on the sample being studied. In mixed-income samples of both men and women, the conclusion is often that neighborhood context has an independent effect on employment outcomes. Briggs (2010) sums up this research by arguing that poor neighborhoods do not simply provide few opportunities (though that is probably the case), but that "the experience of poverty and the prospects for escaping poverty are particularly bad in these places" (p. 39). Research remains divided over whether individual employment outcomes are affected independently by neighborhood conditions (Galster et al. 2010; Brisson et al. 2008) or whether appropriate statistical controls eliminate the effect of neighborhood context (Dujardin and Goffette-Nagot 2010; Katz et al. 200; Kling et al. 2007).

Results derived from samples of single mothers, welfare leavers, and women living in disadvantaged neighborhoods tends to be just as equivocal. Bania et al. (2008) find that job access (having job opportunities in one's neighborhood) matters little for employment. Rather, differences are entirely reducible to individual barriers such as having a disabled child, little prior work history, and so forth. They find that "regardless of the specification, the job access measure used or the dependent variable selected, there is virtually no statistical relationship between job access and labor market outcomes" (p. 31). Gurmu et al. (2008), using a sample of TANF recipients, similarly conclude that "location-related variables [such as poverty rate, living within a quarter mile of public transit, racial composition, and several others] are found to be relatively unimportant." They do conclude, however, that having a driver's license is associated with higher wages and earnings, suggesting that the ability to search for jobs and commute via automobile may provide one important space-related mechanism for better employment outcomes.

On the other hand, Casciano and Massey (2007) conclude that “neighborhood economic circumstances are related to new mothers’ welfare use and employment, above and beyond their individual socioeconomic circumstances.” Baum (2009) comes to a similar conclusion, finding that welfare recipients are significantly more likely to exit the program and become employed if they own a vehicle, suggesting an independent effect of place and mobility. Indeed, owning a vehicle (compared to not owning a vehicle) increases the probability of being employed from 35.9% to 65.3% (though Baum's work does not control for individually-measured factors such as educational attainment, health, etc., that may absorb some of that effect). By contrast, Allard and Danziger (2003) find that greater proximity to employment opportunities is associated both with a higher probability of employment and a higher probability of leaving welfare, both for whites and blacks. If we are to believe these findings, the struggles of disadvantaged women living in poor neighborhoods can be explained by the dearth of job opportunities close to home.

The ambitious Moving to Opportunity (MTO) program, due to its controlled, experimental design, provides probably the best examination to date of the effects of neighborhood context. MTO aimed to shed some light on the contrasting findings mentioned above: would helping those currently housed in public housing developments characterized by concentrated poverty to neighborhoods with less poverty mean better employment outcomes and less use of government assistance programs? In their comprehensive review of the program, Briggs et al. (2010) conclude that it did not have the anticipated effect. In fact, "four to seven years after random assignment, the interim evaluation of MTO found no significant impacts on employment, earnings, or receipt of public assistance across the five MTO sites" (p. 202). There are two main reasons for this finding. First, relocating to a low-poverty neighborhood does not necessarily mean relocating to a job-rich neighborhood (or a neighborhood with jobs hiring for the skill sets that MTO participants possess). Second, there is no guarantee that new neighbors will provide information about job opportunities (indeed, employed MTO participants were somewhat unlikely to have learned about their job from their new neighbors). This can likely be explained, in part, by homophily, or the tendency of people to associate with those like themselves. As Galster (2011) writes,

> "studies consistently show that the social relationships among neighbors of different economic groups are quite limited. Members of the lower status group often do not take advantage of propinquity to broaden their social connections with higher status neighbors and thereby enhance the resource-producing potential of their networks; instead, they often restrict their networks to nearby members of their own group or to those remaining in the "old neighborhood" (p. 227).

Though Galster concedes that social networking may provide some resources in homogenously disadvantaged neighborhoods, their ability to provide those same resources declines in mixed-income neighborhoods. Curley (2010), on the other hand, demonstrates that the ability to form place-based social capital depends just as heavily on the availability of neighborhood resources (libraries, parks, social services, etc.) as it does on the income mix of the neighborhood. Either way, recent research indicates that mobility into a neighborhood with less poverty does not ensure residents' ability to form networks, particularly networks that procure jobs.

Given the failure of the literature to conclude that neighborhood conditions have an independent, measurable effect on employment for disadvantaged urban women, but given the relatively small number of studies and the substantial methodological challenges (discussed below), more investigation is necessary. One plausible conclusion, supported by Coulton (2001) is that disadvantaged women (including welfare program participants and single mothers) cluster in the most disadvantaged neighborhoods. This possibility, though not supportive of the neighborhood effects thesis, opens up possibilities for spatially targeted programs to alleviate hardship and improve employment outcomes. But first, more research is needed into how neighborhoods affect employment outcomes for women, not only whether they do.

Individually Measured Barriers to Employment

A copious body of literature exists on the barriers to employment faced by women in the post-reform era, and most of it focuses entirely on individually-measured barriers to employment. Commonly, analyses unravel the relationship between one particular barrier and an employment outcome. Many of these barriers include childcare and family responsibilities (Baum 2002; Brayfield 1995; Kimmel 1998; Lein and Shexnayder 2007; Romero et al. 2003; England 2005), caring for children with disabilities (Scott 2010), physical health problems or complications (Mullahy and Wolfe 2001; Acs and Loprest 2004; Seccombe and Hoffman 2007), mental health problems (Zabkiewicz and Schmidt 2007; Lee 2005), experiences of domestic violence (Wettersten et al. 2004; Raphael 2000), a lack of crucial skills or work experience (Spivey 2005; Andersson et al. 2005), a lack of access to transportation (Sawicki and Moody 2000; Lacombe 1998; Ihlanfeldt and Sjoquist 1998; Blumenberg and Ong 2001), housing instability (Phinny et al. 2007), and a lack of social networks and social capital that can convey information about opportunities (Newman 1999, p. 77; Edin and Kefalas 2005, p. 174; Elliott 1999; McPherson et al. 2001). The presence of these barriers is widely accepted and well documented.

Through a combination of these individual barriers, many women forced from TANF caseloads following PRWORA's passage simply could not obtain sustainable, living-wage employment (or employment at all). Little research, however, assesses these barriers in conjunction with one another in order to develop a comprehensive picture of the obstacles that disadvantaged women face (see Danziger et al. (2000a; 2000b; Turner et al. 2006; Olson and Pavetti 1996). As important as existing research is, it largely leaves out neighborhood context. Therefore, this paper will weigh individual barriers to employment against one another in order to discern if one particular barrier (i.e., transportation access) stands as the key obstacle, while also producing a more holistic and contextual vision of the situations faced by disadvantaged urban women in the twenty-first century.

Data

The gaps that remain in our understanding of the spatial effects on employment are largely due to methodological constraints. In order to properly understand the effect of space and place over time, researchers require a geographically-linked set of survey data that is longitudinal, and ideally, multi-city. Until recently, no such survey data existed. Then, during 1998-1999, the MDRC (formerly the Manpower Demonstration Research Corporation) undertook an ambitious effort to survey 3,960 women in four U.S. cities who had received AFDC in 1995 and were living in neighborhoods characterized by high rates of poverty and welfare receipt (30 percent and 20 percent, respectively). In the first wave of data collection, most were recent welfare leavers, aged 18-45. The second wave (2001) included follow-up surveys of 3,260 women, 82 percent of the original sample. The resultant dataset, called the Project on Devolution and Urban Change (commonly referred to as "Urban Change") provides the best possible glimpse into the work and personal lives of disadvantaged urban women following welfare reform.

The Urban Change survey data present a unique opportunity for studying the fortunes of poor urban women since welfare reform, however, under special agreement, the MDRC released census tract numbers for each respondent at each wave of data collection. Accordingly, I augment these individual survey data with 2000 U.S. Census data, at the tract level, gleaned from the GeoLytics Neighborhood Change Database. This program contains all long-form Census variables at the tract level from each of the decennial Censuses since 1970. Through use of the NCDB, I am able to include measures such as the tract-level poverty rate, joblessness rate, homeownership rate, car-ownership rate, etc. Because Urban Change data were collected in 1998-1999 and 2001, this analysis uses data from the 2000 Census. Approximately half of the sample (n=1,620) moved tracts between waves.[3] Analyses in this study utilize both waves of data, though only respondents who participated in both waves of data collection are included.[4]

Variables

Dependent Variables

Participants were asked, "Are you currently employed?" without any qualifiers. Previous research suggests that in order to be useful, employment variables must be better operationalized. For example, one of Lein and Shexnayder's (2007) interviewees stated "I still have my job…but I haven't worked since August" (p. 63). Several of their respondents defined sporadic employment with temporary agencies, substitute teacher systems, or on-call services as employment. In order to refine the analysis, the first two models in each table use a variable measuring whether or not

[3] Using neighborhood poverty rate as a rough measure of neighborhood quality, calculated change scores reveal that the neighborhood poverty rate did not fall one bit for movers (average change score -.0002), meaning that on average those who moved relocated to neighborhoods that were every bit as poor as the neighborhoods they left. This suggests that many moves were the result of housing instability, rather than evidence of upward mobility. In short, many moves were parallel moves—into neighborhoods just as poor as the originating neighborhoods.

[4] Additional analyses (not shown) indicate that the group lost by attrition did not differ significantly from those who were retained with regard to any demographic variables.

a respondent reports 1) being employed, 2) earning a wage of at least $5.15 per hour [the federal minimum wage at the time] and 3) working at least 15 hours per week. With a wage of $5.15 and 15 hours per week, an employee could expect a gross annual income of no more than $4,017 per year, roughly one-quarter of the poverty threshold for a family of four ($17,534) or one-third of the threshold for a family of three ($13,874). Falling even below the threshold for one person, this income represents a very low, inadequate income for meeting basic subsistence needs (United States Census Bureau 2011).

The second set of analyses uses a variable measuring whether women are employed in jobs providing at least a wage of $7.75 per hour and at least 35 hours per week. Though arguably still less than it takes to support a family, this type of employment would produce a maximum gross annual income of $14,105. This income exceeds the federal poverty threshold for a family of three (one adult and two children) in 2000, by about $231, but falls short of the threshold for a family of four (one adult and three children) by $3,429. Therefore, models utilizing this dependent variable will be able to parcel out which women succeeded in securing employment with the potential to pull their families out of poverty.

Neighborhood-Level Predictors

Debate exists as to the proper neighborhood-level variables to use for explaining individual outcomes. Research often finds many neighborhood-level variables to be highly correlated, raising the question of how many neighborhood-level constructs or processes truly exist (Sampson et al. 2002:457). Neighborhood effects studies typically include (or recommend including) some combination of neighborhood joblessness and unemployment, percent of persons with incomes below the poverty threshold, percent of families headed by females with children under 18, the percent of males who are unemployed or not in the labor force, residential mobility, housing characteristics, and respondent-observed or interviewer-observed disorder (see Sampson 2001; McNulty 2001; Hannon 2005; Sampson and Raudenbush 2004; Lein and Shexnayder 2007:118).

Following the literature, the neighborhood mechanisms employed here will be:

1) **Poverty:**	Tract Poverty Rate
2) **Joblessness:**	Female Joblessness Rate
3) **Female-Headed:**	Proportion of Families with Children that are Female Headed
4) **Vacancy:**	Proportion of Housing Units that are Vacant
5) **Mobility:**	Proportion of Residents Living in Same House as 5 Yrs Ago
6) **Car Ownership:**	Proportion of Households in Tract that Own a Vehicle
7) **Homeownership:**	Proportion of Owner-Occupied Residential Units
8) **Disorder:**	Index of Interviewer Observed Neighborhood Disorder variables[5]

Though using multiple tract-level measures is often criticized due to potential problems with multicolinearity, simple pairwise correlations (done for both wave 1 and wave 2 data) reveal only modest correlations, ranging from an absolute value of .001 to an absolute value of .659 (most are much lower than .659). In order to minimize the risk of multicolinearity, I also calcuate Cronbach's coefficient alpha for each wave. The wave 1 alpha is .758, and for wave 2, .754. According to Kline (2005, p. 59), this measures the degree to which these variables are representing the same underlying concept. For creating one latent factor, Kline argues that values of .7 are "adequate," meaning they are measuring a similar concept, but not necessarily the same concept. To further eliminate the possibility, I also calculate Variance Inflation Factors (VIF), measuring the extent to which the variance of a coefficient contributes to colinearity. VIF factors are necessarily higher than 1.0, but values larger indicate the effect of multicolinearity on the standard errors (McClendon 1004, p. 162). VIF factors of 4 (and sometimes 10) are usually considered the cutoff for regression modeling, however O'Brien (2007, p. 681) warns that "even

[5] Observed neighborhood disorder is an index composed of four questions asked of interviewers: the presence of 1) "Large groups of teenagers hanging out on the street," 2) "Vacant lots," 3) "Abandoned or boarded up buildings," 4) "Litter," and e) "Vandalism such as broken windows or graffiti." In each item "Yes" is coded as "1" and "No" as "0," making the additive index range from 0 (no disorder) to 5 (high disorder).

when VIF values greatly exceed the rules of 4 or 10, one can often confidently draw conclusions from regression analyses). No variables in this analysis individually exceed the 4.0 or 10.0 cutoffs. O'Brien also suggests average VIFs (for all variables taken together) of about 2.0; much higher VIFs indicates possible colinearity issues. When all variables in the models (including the individual-level variables discussed below) are taken together, it yields VIF averages of 2.05 (Wave 1 data) and 2.08 (Wave 2), almost exactly at O'Brien's cutoff.

Individual-Level Predictors

All analyses include a number of individual-level predictors, all of which are included to test for (and to control for) the individual-level barriers that other research has found to be important for understanding the labor market activity of disadvantaged urban women in the post-welfare reform era. Table 1 provides the original question asked of respondents for each variable, and (if applicable) notes about coding.

[Table 1 here]

Methods

Despite the theoretical reasons why neighborhoods matter for individuals, academic inquiry into neighborhood effects faces several major obstacles. Primarily, neighborhood research, multi-level by nature, is prone to the self-selection and clustering criticisms. The problem is simply that neighborhoods contain individuals who are very similar in many measured and unmeasured ways including background socioeconomic status, attitudes toward education, childbearing and employment. Therefore, deciphering which effects stem from the neighborhood context and which effects stem from pre-existing, unmeasured similarities between residents is difficult, conceptually and statistically. Furthermore, individuals are not randomly assigned to neighborhoods; rather, they choose neighborhoods subject to prices and income (housing affordability, information accessibility, and discrimination limit this "choice"). A group of people living in a "bad" neighborhood will likely have some unobserved characteristics in common (characteristics that affected their likelihood of inhabiting that neighborhood). The observed effect is therefore spurious. In quantitative terms, all of the un-modeled contextual information ends up pooled into the single individual error term of the model. Individuals of the same neighborhood will have correlated errors, violating the basic regression assumption of independence (Luke 2004:7).

Common approaches to ameliorating this problem include the utilization of a robust standard error correction (Elliott 1999a) and the use of only a very limited number of individuals per geographic unit (Haney 2007), both of which are incorporated into the following analyses.

Much prior neighborhood research relies on cross-sectional data, but, as Lee (2001:37) points out, "the causal terrain is more rugged than this" and that cross sectional data take a "slice out of a cyclical process." Consequently, this research relies on a series of logistic regression models, predicting the likelihood or odds or a particular employment outcome occurring, versus that outcome not occurring. It also relies on a slightly more sophisticated modeling strategy necessitated by the longitudinal nature of the study. Following the recommendation of Halaby (2004) and Finkel (1995), this research utilizes lagged endogenous variables, where the Wave 2 dependent variable (Y_t) is predicted not only by a range of Wave 1 or Wave 2 independent variables, but by an earlier value of Y, here denoted as Y_{t-1}. Such a strategy is appropriate when the dependent variable may theoretically be dependent, at least in part, upon its earlier values. Halaby (2004:536) calls this a model of "state dependence" where there exists a causal effect of past values of the response variable on current values (i.e., holding employment at Wave 1 makes it more likely that a respondent will hold employment at Wave 2). This model may be characterized as,

$$Y_t = b_0 + b_1X_t + b_2Y_{t-1} \square\square\square e_t$$

Beyond modeling state dependence, research more typically uses a lagged endogenous approach to rectify estimation problems such as unobserved confounding variables and heterogeneity bias (the confounding effect of unmeasured time-invariant variables that are omitted from the regression model). The lagged endogenous variable approach also serves a theoretical purpose, as employment in 2001 will logically be dependent upon prior employment, assuming that employers look more favorably upon work experience (see Andersson et al. 2005; Heckman and Krueger 2005; Spivey 2005; Theodos and Bednarzik 2006), and assuming that many women will be able to retain employment between waves.

Results

Table 2 presents four cross-sectional (Wave 2 -- 2001) logistic regression models. Model 1 regresses whether or not women have a job that pays at least a $5.15 hourly wage and provides at least 15 hours per week on women's neighborhood characteristics. The second models the same dependent variables but includes individual-level covariates. The third and fourth models utilize a dependent variable measuring whether or not women held a job with at least a $7.75 wage and 35 hours per week. These models set the stage for the analyses that follow by demonstrating the overall effect of neighborhood characteristics on employment outcomes, though the use of a composite neighborhood index.[6] Although Tables 3 and 4 will explore how

[6] The seven Census-derived neighborhood variables used in the analysis are, in this case, compiled into an additive index where a higher score indicates neighborhood conditions that are viewed by the literature as detrimental to employment (and many other outcomes). To achieve this, the homeownership rate and car ownership rate are first reverse-coded.

and why neighborhood conditions affect employment, these models demonstrate that a neighborhood effect exists only for higher paying jobs that provide more working hours. This effect is negative, whereby residence in a neighborhood with higher poverty, less car ownership, more joblessness, etc., is associated with decreased odds of holding a job with at least a $7.75 hourly wage and 35 hours per week of employment. This effect, however, disappears when individual controls are added in Model 4. Therefore, while residence in a disadvantaged neighborhood is associated with lower odds of employment, this effect is explained away by a rather exhaustive list of individually measured circumstances, suggesting that neighborhood mechanisms are associated with employment, but may not cause these (or may be a distal, rather than a proximate, cause).

The analyses in Table 3 expand upon Table 2 by unpacking the neighborhood index and utilizing the seven neighborhood-level predictors separately. As such, the model contains four cross-sectional logistic regression models, using dependent and independent variables measured in 2001.

[Table 3 here]

Results of Model 1 indicate that female headedness, roughly reflecting the proportion of single-parent families in the neighborhood, is a significant and positive predictor of holding a job with at least a $5.15 wage and 15 hours of work per week. In other words, women who live in neighborhoods with more single parent families are actually more likely to hold a job. Though female headedness is often used in research as a marker of neighborhood disadvantage, results indicate that women living in neighborhoods with high rates of single-parent families actually did better in terms of employment.[7] This may relate to the development of strong support networks of single mothers that can develop and provide necessary services (childcare, transportation assistance, etc.) for one another (see Stack 1974; Edin and Kefalas 2005). This effect, however, does not remain significant when individual controls are added in Model 2 and it is explained away by other factors. Additionally, the level of interviewer-observed disorder is significant and negative, meaning that women in more disordered neighborhoods are less likely to hold a job with at least that wage and hours of work per week. Like the above effect, it fails to hold when individual controls are taken into account. The same conclusions can be made from Models 3 and 4, which model the likelihood of having a job with at least a $7.75 wage and 35 hours of work per week. The one exception is that the female joblessness rate is significant and negative, suggesting that women who live in neighborhoods where more women are unemployed or out of the labor force are less likely to be employed themselves.

Table 3 also indicates that several individual factors are predictive of employment. Most notably, having lived during their own childhoods in families that received AFDC decreased women's likelihood of having a job with at least a $5.15 wage and 15 hours per week (though not the odds of having a $7.75/35 job). This finding suggests the presence of an inter-generational effect of poverty, even while controlling for numerous individual and neighborhood factors. Childcare and family responsibilities also prove important with currently being pregnant, having a greater number of coresident children, having a child under six years old, and having a child with a disability all decreasing the odds of one or both employment outcomes. Finally, owing a car is one of the most important predictors. Women whose household owns a car are more than twice as likely to have a job with at least a $5.15 wage and 15 hours per week as women without

[7] Readers should take care not to interpret this finding such that *being* a single-mother is associated with greater odds of employment. Due to the multi-level nature of the study, the correct interpretation is that *living in a neighborhood* with more single-mothers is associated with greater odds of employment.

a car. Likewise, women with a car are 2.2 times as likely to have a job with at least a $7.75 wage and 35 hours per week as women without a car. Though having a car is important for securing any employment, it clearly matters more for securing higher paying jobs with more hours. Presumably, having a car increases a woman's potential job search and commuting radius, allowing women to seek out better opportunities. It also facilitates reliable travel between home, work, and childcare arrangements.

The longitudinal nature of the Urban Change data provide the opportunity to assess how neighborhood conditions and individual characteristics at one point in time affect employment two years later. Table 4 provides similar regression models as above, but with all independent variables measured in 1999 and the dependent variables measured in 2001. It also includes a lagged endogenous variable, measuring whether a particular woman had a job with those particular characteristics two years earlier (in other words, the dependent variable measured at Wave 1). Lastly, these models include two dummy variables representing whether women in the sample moved to a neighborhood with a lower poverty rate between waves or moved to a tract with a higher poverty rate. The excluded reference category is women who did not move between waves (or moved to a neighborhood with the exact same poverty rate as their originating neighborhood). These are included in order to assess whether women who moved into lower poverty neighborhoods saw improved labor market outcomes.

[Table 4 here]

Model 1 again reveals the positive effect of living in a neighborhood with a high rate of female-headedness on having a job with at least a $5.15 wage and 15 hours per week, though this effect again disappears when individual predictors are added. Interestingly, the neighborhood car ownership rate is significant and positive, suggesting that women who live in neighborhoods with more cars in 1999 are more likely to hold employment in 2001, however this same effect fails to hold when considering higher-quality ($7.75 and 35 hours) employment. Once again, individual car ownership is significant and the magnitude of the effect increases along with the quality of the employment. Therefore, while neighborhood car ownership matters more for holding at least a low-earning job two years later, individual car ownership matters more for holding a better quality job two years later. Clearly, relying on neighbors for transportation does not help to secure and retain higher-paying jobs, but does help in lower-paying jobs with fewer hours.

The unimportance of neighborhood social capital is visible in assessing the effect of neighborhood vacancy rate on holding either type of job. While traditional models of disadvantage (Sampson et al. 2002) suggest that a high vacancy rate is predictive of disadvantage, to the extent that vacancy impedes the ability to form neighborhood-based social capital, here the effect is positive; women who live in neighborhoods with a higher proportion of vacant buildings are more likely to hold a job with at least a $7.75 wage and 35 hours per week than women in low-vacancy neighborhoods. Similarly, they are also more likely to hold lower paying jobs with fewer hours, but this effect is significant at only the $p<.10$ level. Though neither of these findings hold when individual controls are added, it does mean that women in higher-vacancy neighborhoods are more likely to hold a job *two years later* than women in lower-vacancy neighborhoods.[8] One possible explanation could be less competition for jobs in areas with less population density.

[8] Although vacancy rate is correlated negatively with the odds of employment (as could be expected) and is correlated positively with other indicators of neighborhood problems (such as the poverty rate), once it is placed into regression models and subjected to statistical control, the net effect of vacancy is positive, meaning that the negative relationship between vacancy and employment is explained away by controlling for other factors (presumably the other neighborhood characteristics). At that point, the net effect of vacancy is positive, but only borderline-significant ($p<.0498$). In sum, there is not enough evidence to argue from this finding that vacancy promotes employment. It indicates that, all else equal (which it almost never is), those in higher vacancy neighborhoods in

The homeownership rate is not significant in any of the models. Previous research finds that a high rate of homeownership help interactions to "gel over time to create the form and consequences of the social climate of the community" (Schieman 2005: 1033). Even if homeownership helps neighbors to "gel over time," there is no evidence suggesting that this process translates into tangible differences in employment outcomes.

The poverty rate is not significant in these models (or those in Table 3). Since these are the most commonly used variables in "neighborhood effects" studies, findings here indicate the need for studies that unpack the specific neighborhood mechanisms at work, rather than simply chalking them up to problems associated with neighborhood poverty, which is often cast as a "black box" (Jencks and Mayer 1990).

Overall, the model indicates that several of the neighborhood characteristics operate in a temporally lagged fashion; while neighborhood car ownership did not matter for employment cross-sectionally once individual controls were added, the car ownership rate in one's neighborhood affects job prospects two years later. The finding suggests that many of the cross-sectional "neighborhood effects" studies cannot grasp the effect of context on employment because they do not always occur contemporaneously.

Finally, the model includes a variable measuring whether a woman changed Census tracts between waves. Results in Models 3 and 4 indicate that women who moved to a neighborhood with a lower poverty rate were more likely to hold a job with at least a $7.74 wage and 35 hours per week at Wave 2 than women who did not move. This finding suggests that there may be some benefit to relocating to a neighborhood that provides more ample employment opportunities. Interestingly, however, the reverse is not true; women who moved to

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1999 were more likely to hold employment two years later (2001). This rather curious finding certainly deserves future attention, but it appears that the effect is reducible to individual-level factors.

neighborhoods with a higher poverty rate did not have worse outcomes than women who did not relocate.

Because this model utilizes 1999 predictors and a 2001 dependent variable, it also includes a lagged endogenous variable (the dependent variable in 1999). Also referred to as the stability effect of employment, this variable tells us that women who held jobs with at least a $5.15 wage and 15 hours of work per week in 1999 were 4.5 times more likely to have such a job in 2001 than women who did not hold one in 1999. The magnitude of the effect is decreases to 3.7 when all individual controls are added. Similarly, Models 3 and 4 reveal that this effect can be seen for better quality jobs, as well; women who held a job with at least a $7.75 wage and 35 hours per week in 1999 were about 3 times more likely to hold such a job in 2001 as women who did not hold one in 1999. This effect likely stems from complementary processes; while women who held jobs in 1999 were often able to keep their jobs over two years, even those who were not able to retain their jobs presumably benefited from the human capital built through work experience, subsequently obtaining another similar job (see Holzer 1999).

The individual effects in Models 2 and 4 again reveal the effect of health, whereby better health and less depression result in better employment outcomes. As above, heavier childcare responsibilities inhibit employment. And again, car ownership increases the probability of having a job with at least a $5.15 wage and 15 hours per week by a factor of 1.2, while it increases the odds of having a job with at least a $7.75 wage and 35 hours per week by a factor of 1.5. Contrary to the common portrayal of black women as eschewing employment for welfare (Quadagno 1996), Model 2 reveals that, all else equal (which it rarely is), African American women are 1.5 times *more* likely than white women to hold a job with at least a $5.15 wage and 15 hours per week. Though this effect does not persist when looking at better quality jobs (effect significant at only p<.10), it does suggest that the racialized discourse about work and welfare is misguided and should be challenged. Finally, women living in Los Angeles and Miami have a lower odds of both types of jobs than women living in Cleveland (the excluded reference category). This finding points to very different labor markets in each city; similarly-qualified women face better job prospects in Philadelphia and Cleveland, and comparatively fewer opportunities in Miami and Los Angeles.

Conclusions

This study provides entrée into the interplay between individually measured barriers to employment (health, childcare responsibilities, domestic violence, human capital, etc.) and contextual barriers to employment (neighborhood poverty, joblessness, vacancy, car ownership, etc.), with special attention paid to how neighborhood conditions help to explain employment outcomes before and after the addition of individual controls.

Results indicate that a few neighborhood conditions are predictive of employment. In several cases, significant effects that are observed are explained away by adding a relatively exhaustive cadre of individual barriers to employment and demographic characteristics. This finding suggests that individually measured barriers to employment act as proximate causes of employment, while neighborhood conditions (to the extent they matter at all) must operate as more distal causes, through their influence on individually-measured barriers. There are two key exceptions to this: One involves the effect of neighborhood car ownership. Having more vehicles in the neighborhood helps women's abilities to hold at least a low-paying job with few hours of work per week. It does not appear to affect the acquisition or retention of better jobs. Given that the effect of individual car ownership seems strong and robust, future research should explore the interplay between neighborhood car ownership and individual car ownership in securing and retaining employment. The other effect involves neighborhood joblessness, whereby women in neighborhoods with a higher female joblessness rate are less likely to hold employment themselves, even controlling for a relatively exhaustive list of individually-measured characteristics and situations. This suggest that some neighborhoods provide fewer job opportunities for their residents, forcing women to remain jobless or unemployed, or to search for work far away from home (resulting in increased transportation and childcare costs). Results also indicate that women in higher poverty neighborhoods see somewhat improved labor market outcomes by moving to neighborhoods with less poverty.

The strongest findings involve the effect of individually measured factors on employment outcomes. Having received AFDC during their own childhoods affects women's ability to hold employment, suggesting an intergenerational transfer of disadvantage that ought to be more fully explored. Likewise, not owning a car, suffering from health problems or depression, not having a high school diploma, having more onerous childcare responsibilities, and living particular local labor markets (Miami and Los Angeles) all have significant, deleterious effects on employment.

Though the longitudinal, geographically-focused, multi-city nature of this study makes it unique, several additional problems must be addressed in future research. First, we know that the quality of employment is a complicated matter and that wages and working hours only begin to help us understand women's labor market outcomes (Kalleberg et al. 2000). Second, although the Urban Change data contain information on the group most affected by welfare reform, not all women in the study left welfare at the same time, meaning that in both 1999 and 2001, some had just left TANF while others had left years earlier. Comparing women at the same point in the welfare-to-work transition would provide a more sophisticated analysis of barriers to employment. Third, although the study relies on the number of hours employed women work per week, I assume that women in the dataset accepted any hours that they were offered. Some women may have in fact turned down additional working hours, owing to childcare or other responsibilities. Fourth, the neighborhood conditions and characteristics utilized here only begin to touch on the possible ways in which urban context affects individual outcomes. Still limited by the neighborhood-level data made available by the U.S. Census bureau, social research requires better data on employment opportunities, transportation access, childcare availability, and many other neighborhood characteristics that can and should affect employment.

From a policy standpoint, the disappearance of several neighborhood effects following the addition of individual controls is telling, and suggests that individuals are affected by their neighborhood contexts in perhaps more nuanced ways than census-derived measures of homeownership or vacancy can reveal. The significant neighborhood coefficients in the neighborhood-only models (Models 1 and 3 in Tables 3 and 4) suggest that women who experience less success in the labor market and more individually-measured disadvantages (health problems, etc.) are also clustered in neighborhoods with particular conditions (fewer cars, more disorder, etc.). In this sense, neighborhoods can be viewed best as containers, not as emergent, causal factors. This does not mean that neighborhood context can be ignored by public policy, however. On the contrary, the clustering of individual disadvantage opens possibilities for spatially-targeted policies aimed at channeling resources into disadvantaged neighborhoods, ostensibly to address individual problems and disadvantages. This could include, for example, funding for low-cost, subsidized neighborhood childcare centers. Having such centers in low-income areas would address both the childcare barriers and the importance of car ownership, as for many women it would mean shorter, easier commutes if quality, low-cost childcare options existed close to home. It should also include providing incentives for employers to relocate to higher-joblessness neighborhoods or the creation of better transportation alternatives to help residents of poor neighborhoods find and secure jobs in other neighborhoods. All of these policy initiatives should be spatially-targeted. Although neighborhood conditions are not the clear problem, neighborhood initiatives can be the solution.

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Table 1. Original Instrument Questions for and Descriptive Statistics for All Independent Variables.

Variable	Questions from Instrument	Descriptive Statistics, Wave 1	Descriptive Statistics, Wave 2
Neighborhood Characteristics			
Poverty Rate	Proportion of Tract Residents Below Poverty Line [Census]	Mean = .350 s.d. = .133	Mean = .333 s.d. = .137
Female Headedness Rate	Proportion of Tract Households that are Female Headed [Census]	Mean = .525 s.d. = .184	Mean = .506 s.d. = .184
Female Jobless Rate	Proportions of Female Tract Residents who are Jobless [Census]	Mean = .599 s.d. = .092	Mean = .592 s.d. = .094
Mobility Rate	Proportion of Tract Residents Lived in Home Less than 5 Years [Census]	Mean = .544 s.d. = .126	Mean = .550 s.d. = .126
Vacancy Rate	Proportion of Tract Housing Units Vacant [Census]	Mean = .126 s.d. = .076	Mean = .117 s.d. = .069
Car Ownership Rate	Proportion of Households in Tract that Own at least 1 Vehicle [Census]	Mean = .649 s.d. = .173	Mean = .666 s.d. = .175
Homeownership Rate	Proportion of Tract Homes that are Owner-Occupied [Census]	Mean = .436 s.d. = .196	Mean = .455 s.d. = .202
Moved to N'Hood with Less Poverty	Calculated for those who changed tracts between waves	N.A.	Yes = 31.9% No = 68.1%
Moved to N'Hood with More Poverty	Calculated for those who changed tracts between waves	N.A.	Yes = 20.2% No = 79.8%
No Move or Same Poverty Rate	Calculated for those who changed tracts between waves	N.A.	Yes = 47.9% No = 52.1%
Disorder Index	Within one or two blocks of R's home, were there any of the following things? [0=No; 1=Yes] a. Large groups of teenagers hanging out on the street? b. Vacant lots? c. Litter and garbage on the street or sidewalk? d. Abandoned or boarded up houses or buildings? e. Vandalism such as broken windows or graffiti? [Added into an index, ranging from 0 to 5].	Mean = 1.99 s.d. = 1.96	Mean = 1.57 s.d. = 1.82
Demographics			
Age	What is your date of birth? (recoded into years of age)	Mean = 33.65 s.d. = 7.01	N.A.
Race	a. White b. Black/ African American. c. Hispanic/Latino d. Other Race	White = 5.0% Black = 68.8% H/L = 24.6% Other = 1.6%	N.A.
Foreign Born	What is your place of birth? (0=U.S.; 1=Elsewhere)	Foreign Born = 18.1% Native Born = 81.9%	N.A.
Childhood AFDC	Did your family receive AFDC benefits	Yes = 45.6%	N.A.

	at any time before you turned 18?	No = 54.4%	
Human Capital			
H.S. Diploma or GED	Do you have a high school diploma or a GED certificate?	Yes = 51.3%	Yes = 57.4%
Associate's Degree (or higher)	What is the highest grade or level of school or college you have ever completed (Associate's, 4 years of college/Bachelor's degree, graduate degree).	Yes = 3.6%	Yes = 3.6%
Trouble Understanding English	How well do you understand a conversation in English? (0=Very well or Well [No]; 1=Some/Little/Not at all [Yes])	Yes = 8.4% No = 91.6%	Yes = 8.2% No = 91.8%
Family Responsibilities			
Current Marital Status	Are you currently: married and living with your husband, separated or living apart from your husband, divorced, widowed? (1=Married; 0=Not married)	Married = 9.0% Not Married = 91.0%	Married = 14.3% Not Married = 85.7%
Cohabiting	Are you currently living with a boyfriend or partner as a couple?	Yes = 24.0% No = 76.0%	Yes = 27.9% No = 72.1%
Pregnant	Are you currently pregnant?	Yes = 3.7% No = 96.3%	Yes = 2.4% No = 97.6%
Number of Children	In the past month, how many of your own children were living at home with you?	Mean = 2.44 s.d. = 1.36	Mean = 2.39 s.d. = 1.42
Child Under Six	Please tell me (Child A, B, C, etc)'s birthdate, beginning with the month. (1=Has child under six; 0=Does not).	Yes = 54.7% No = 42.6%	Yes = 37.4% No = 62.6%
Child with Disability	Does your child (do any of your children) have an illness or disability that demands a lot of your attention and makes it hard for you to work or go to school?	Yes = 18.2% No = 81.8%	Yes = 15.2% No = 84.8%
Health			
Self-Reported Health	Would you say your health is excellent (5), very good (4), good (3), fair (2), or poor (1)?	Mean = 3.30 s.d. = 1.15	Mean = 3.21 s.d. = 1.15
CESD Depression Score	Composite score (60-point scale) from multiple questions aimed at detecting high levels of clinical depression	Mean = 17.81 s.d. = 11.57	Mean = 17.09 s.d. = 11.71
Violence	Has someone hit, slapped, kicked, or otherwise physically harmed you in the past year?	Yes = 7.3% No = 92.7%	Yes = 6.4% No = 93.6%
Alcohol Use	Please tell me how often each of the following statements was true during the past thirty days: I drank enough alcohol, including beer, wine, wine coolers, or liquor, to get drunk. (0=never; 1=once or twice; 2=3 to 5 times; 3=6 to 10 times; 4=more than 10 times).	Mean = .381 s.d. = .732	Mean = .400 s.d. = .762
Drug Use	I used cocaine or crack, heroin, PCP or ice (1= At least once in past month; 0=Not at all in the past month)	Yes = 2.2% No = 97.8%	Yes = 2.5% No = 97.5%
Networks			

Network Index	a. In past month, did you receive any money from family or friends outside the household/family to help pay for living expenses? b. Did you take in family or friends because they needed a place to live? c. How did you use [your] tax [return] money? (option: loaned or gave money to friend or relative) [Each item coded as 1=Yes; 0=No; Added into Index with possible range 0 to 3].	Mean = .235 s.d. = .462	Mean = .238 s.d. = .473
Transportation			
Car Ownership	Do you or anyone in your household/family own a car, van, truck, not including RV's or motorcycles?	Yes = 37.1% No = 62.9%	Yes = 50.0% No = 50.0%
Housing and City			
Housing Stability	Have you had trouble finding a good place to live in last year?	Yes = 27.7% No = 72.3%	Yes = 25.0% No = 75.0%
Subsidized Housing	Does your household pay less rent because the government pays for part of it, such as in Section 8 housing?	Yes = 45.1% No = 54.9%	Yes = 29.5% No = 70.5
City of Residence	a. Cleveland b. Los Angeles c. Miami d. Philadelphia	Cleveland = 26.6% Los Angeles = 23.7% Miami = 24.3% Philadelphia = 25.4%	N.A.

Table 2. Cross-Sectional Logistic Regression Models Predicting Two Employment Outcomes in 2001, with Neighborhood Index

(Odds Ratios Provided, Robust Standard Errors in Parentheses)

DV:	$5.15 and 15 Hours/Week		$7.75 and 35 Hours/Week	
	Model 1	Model 2	Model 3	Model 4
N'Hood Index	0.943	1.012	0.842***	0.895
	(0.057)	(0.069)	(0.052)	(0.065)
N'Hood Disorder	0.939***	0.979	0.957*	0.988
	(0.020)	(0.024)	(0.022)	(0.026)
Age		0.972***		0.972***
		(0.007)		(0.007)
Black		1.445*		1.330
		(0.283)		(0.277)
Hispanic		1.143		1.163
		(0.259)		(0.278)
Other Race		1.146		1.358
		(0.455)		(0.531)
Foreign Born		1.304		1.194
		(0.229)		(0.209)
AFDC as Child		0.798**		0.871
		(0.073)		(0.082)
H.S. Dip or GED		2.062***		2.009***
		(0.174)		(0.187)
Assoc. Degree		3.230***		3.263***
		(0.835)		(0.771)
Trb. Und. Eng.		0.779		0.389***
		(0.155)		(0.091)
Married		0.885		1.121
		(0.140)		(0.175)
Cohabiting		1.195		0.978
		(0.149)		(0.123)
Pregnant		0.512***		0.785
		(0.127)		(0.214)
Num. of Children		0.949		0.933**
		(0.030)		(0.031)
Child under Six		0.761***		0.884
		(0.077)		(0.093)
Disabled Child		0.713***		0.666***
		(0.081)		(0.084)
Self-rated Health		1.258***		1.148***
		(0.051)		(0.047)
Depression Scale		0.981***		0.979***
		(0.004)		(0.004)
Suffer Violence		0.576***		0.563***
		(0.097)		(0.111)
Drinking		1.140**		1.058
		(0.065)		(0.063)
Drug Use		0.479***		0.613
		(0.132)		(0.193)

Network Index		0.879		0.943
		(0.074)		(0.087)
Owns a Car		2.117***		2.237***
		(0.181)		(0.204)
Trb. Find House		1.109		1.021
		(0.107)		(0.107)
Subsidize House		0.775***		0.605***
		(0.069)		(0.060)
Los Angeles		0.602***		0.706***
		(0.073)		(0.090)
Miami		0.614***		0.549***
		(0.073)		(0.068)
Philadelphia		0.829		1.087
		(0.095)		(0.130)
Constant	1.719***	1.610	0.867	1.096
	(0.299)	(0.704)	(0.155)	(0.497)
Observations	3202	3202	3202	3202
Pseudo R^2	0.00302	0.126	0.00416	0.131

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Cross-Sectional Logistic Regression Models Predicting Two Different Employment Outcomes in 2001
(Odds Ratios Provided, Robust Standard Errors in Parentheses)

DV:	**$5.15 and 15 Hours/Week**		**$7.75 and 35 Hours/Week**	
	Model 1	Model 2	Model 3	Model 4
NH Poverty	0.762*	1.027	0.785	1.046
	(0.118)	(0.176)	(0.124)	(0.182)
NH Fem.-Head	1.724***	1.180	1.373**	0.943
	(0.261)	(0.216)	(0.219)	(0.177)
NH Fem. Jobless	1.042	1.311	0.472**	0.640
	(0.364)	(0.496)	(0.173)	(0.256)
NH Moved 5 Yrs	0.923	0.972	0.877	0.926
	(0.175)	(0.214)	(0.171)	(0.203)
NH Units Vacant	1.041	0.975	1.018	0.917
	(0.090)	(0.096)	(0.091)	(0.094)
NH HH with Car	1.434*	1.184	0.929	0.855
	(0.281)	(0.299)	(0.193)	(0.240)
NH Homeown	1.064	1.081	1.149*	1.063
	(0.082)	(0.095)	(0.097)	(0.102)
NH Disorder	0.936***	0.978	0.950**	0.990
	(0.021)	(0.024)	(0.022)	(0.026)
Age		0.972***		0.972***
		(0.007)		(0.007)
Black		1.394*		1.327
		(0.279)		(0.283)
Hispanic		1.119		1.166
		(0.255)		(0.281)
Other Race		1.112		1.372
		(0.444)		(0.540)
Foreign Born		1.336		1.195
		(0.236)		(0.210)
AFDC as Child		0.796**		0.875
		(0.073)		(0.083)
H.S. Dip or GED		2.071***		2.007***
		(0.175)		(0.187)
Assoc. Degree		3.226***		3.253***
		(0.834)		(0.768)
Trb. Und. Eng.		0.775		0.389***
		(0.154)		(0.091)
Married		0.888		1.119
		(0.141)		(0.175)
Cohabiting		1.190		0.979
		(0.148)		(0.124)
Pregnant		0.513***		0.783
		(0.128)		(0.212)
Num. of Children		0.947*		0.934**
		(0.030)		(0.032)
Child under Six		0.764***		0.887

		(0.078)		(0.093)
Disabled Child		0.714***		0.661***
		(0.081)		(0.083)
Self-rated Health		1.258***		1.147***
		(0.051)		(0.047)
Depression Scale		0.981***		0.980***
		(0.004)		(0.004)
Suffer Violence		0.569***		0.562***
		(0.096)		(0.111)
Drinking		1.135**		1.060
		(0.065)		(0.063)
Drug Use		0.481***		0.610
		(0.133)		(0.193)
Network Index		0.878		0.943
		(0.074)		(0.087)
Owns a Car		2.114***		2.231***
		(0.181)		(0.204)
Trb. Find House		1.105		1.025
		(0.106)		(0.108)
Subsidize House		0.787***		0.595***
		(0.071)		(0.060)
Los Angeles		0.615***		0.705**
		(0.092)		(0.109)
Miami		0.600***		0.550***
		(0.076)		(0.074)
Philadelphia		0.832		1.043
		(0.119)		(0.157)
Constant	2.098**	2.498*	0.349***	0.482
	(0.656)	(1.362)	(0.114)	(0.272)
Observations	3,202	3,202	3,202	3,202
Pseudo R-squared	0.00963	0.127	0.0121	0.131

*** p<0.01, ** p<0.05, * p<0.1

Table 4. Logistic Regression Models Predicting Two Different Employment Outcomes in 2001, Using Lagged 1999 Predictors.
(Odds Ratios Provided, Robust Standard Errors in Parentheses)

DV:	**$5.15 and 15 Hours/Week**		**$7.75 and 35 Hours/Week**	
	Model 1	Model 2	Model 3	Model 4
DV in 1999 (Yt-1)	4.550***	3.760***	4.296***	3.188***
	(0.366)	(0.324)	(0.420)	(0.331)
Moved – Less Poverty	0.989	0.991	1.215**	1.233**
	(0.088)	(0.092)	(0.111)	(0.118)
Moved – More Poverty	1.048	1.132	1.036	1.116
	(0.109)	(0.125)	(0.111)	(0.128)
NH Poverty	0.885	1.236	0.768	1.116
	(0.156)	(0.228)	(0.139)	(0.213)
NH Fem.-Headedness	1.444**	1.051	1.056	0.695*
	(0.238)	(0.202)	(0.178)	(0.138)
NH Fem. Jobless	0.996	1.177	0.642	0.919
	(0.391)	(0.493)	(0.256)	(0.404)
NH Moved 5 Yrs	0.802	0.661*	0.756	0.653*
	(0.163)	(0.158)	(0.156)	(0.155)
NH Units Vacant	1.193*	1.131	1.278**	1.180
	(0.111)	(0.115)	(0.126)	(0.127)
NH HH with Car	1.800***	2.316***	1.114	1.573
	(0.381)	(0.648)	(0.239)	(0.473)
NH Homeownership	1.077	1.025	1.065	0.968
	(0.088)	(0.098)	(0.097)	(0.097)
NH Disorder	0.983	0.990	0.984	0.988
	(0.023)	(0.024)	(0.023)	(0.025)
Age		0.986*		0.980**
		(0.007)		(0.008)
Black		1.487**		1.433*
		(0.295)		(0.297)
Hispanic		1.315		1.315
		(0.297)		(0.307)
Other Race		0.991		1.451
		(0.417)		(0.560)
Foreign Born		1.304		1.210
		(0.222)		(0.207)
AFDC as Child		0.742***		0.806**
		(0.067)		(0.077)
H.S. Dip or GED		1.460***		1.688***
		(0.124)		(0.151)
Assoc. Degree		1.488*		1.546*
		(0.353)		(0.344)
Trb. Und. Eng.		0.649**		0.396***
		(0.121)		(0.088)
Married		0.986		0.906
		(0.175)		(0.157)
Cohabiting		0.969		1.039

		(0.110)		(0.115)
Pregnant		0.990		1.073
		(0.210)		(0.219)
Num. of Children		0.938**		0.940*
		(0.030)		(0.032)
Child under Six		1.162		1.105
		(0.119)		(0.118)
Disabled Child		0.753***		0.703***
		(0.078)		(0.081)
Self-rated Health		1.232***		1.163***
		(0.049)		(0.047)
Depression Scale		0.989***		0.986***
		(0.004)		(0.004)
Suffer Violence		0.894		0.992
		(0.139)		(0.164)
Drinking		0.948		0.995
		(0.058)		(0.065)
Drug Use		1.040		0.757
		(0.309)		(0.271)
Network Index		1.055		1.170*
		(0.099)		(0.109)
Owns a Car		1.213**		1.494***
		(0.115)		(0.140)
Trb. Find House		0.869		0.882
		(0.084)		(0.092)
Subsidize House		0.940		0.973
		(0.088)		(0.097)
Los Angeles		0.582***		0.584***
		(0.091)		(0.098)
Miami		0.747**		0.637***
		(0.096)		(0.087)
Philadelphia		1.168		1.321*
		(0.179)		(0.210)
Constant	1.531	1.546	0.345***	0.440
	(0.514)	(0.834)	(0.120)	(0.243)
Observations	3188	3188	3188	3188
Pseudo R-squared	0.0989	0.142	0.0672	0.123

*** p<0.01, ** p<0.05, * p<0.1

Author Biography

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