The Multigenerational Transmission of Neighborhood Disadvantage

Population Association of America
2019 Annual Meeting Proposal

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Abstract: Empirical examinations of how residential inequality compounds over multiple generations are rare. This project conceptualizes inequality as a process that spans multiple generations and investigates the intergenerational transmission of neighborhood disadvantage. Restricted tract-level data from the National Longitudinal Survey of Youth 1979 cohort and from the Child and Young Adult cohort will for an empirical investigation into how multiple generations of neighborhood disadvantage affects neighborhood diadvantage in adulthood. In addition to multivariate regression models, the kinship structure of these data allows for cousin fixed effects models that control for unobserved confounders operating at the extended family level. Preliminary findings demonstrate that exposure to neighborhood disadvantage in parent's childhood and in grandchildren's childhood increases grandchildren's chances of living in a disadvantaged neighborhood in adulthood. Moreover, the results indirectly suggest that neighborhoods may impact inequality across four generations of a family by limiting the chilchood context of opportunity of great-grandchildren. This analysis contributes to a more robust understanding of the role that neighborhoods play in the persistence of inequality across multiple generations.

Background: The Census Bureau counted more than 13 million children living in poverty[1] in the United States in 2016, or roughly 18% of all children (U.S. Census Bureau 2017). The number of children living in deep poverty, defined as having a family income of less than half the poverty line, has grown sharply since welfare reform over two decades ago (Shaefer and Edin 2014; Duncan and Magnuson 2011). Poverty's envelopment of children has corresponded with an entrenchment of poverty in certain neighborhoods that endures, even when accounting for political efforts to eradicate it and individual- and family-level residential mobility (Sharkey 2013). Children live in more unequal residential environments than adults (Owens 2016) and this persistence of disadvantaged neighborhood conditions contributes to experiences of hardship and inequality across the life course. Single generation effects can transform into multigenerational effects through a pernicious cycle as neighborhood conditions are passed onto children and future progeny.

The study of intergenerational exposure to neighborhood contexts is essential for our understanding of inequality in the United States (Mare 2011; Massey 2013). To that end, this paper explores how neighborhood disadvantage gets passed down across successive generations of respondents to the National Longitudinal Survey of Youth (NLSY).. Specifically, our analytic focus is the relationship between multigenerational exposure to neighborhood disadvantage (in both the grandparent's adulthood and the parent's adulthood) and the subjective neighborhood assessment of the grandchildren in adulthood. Empirically, very little research has explicitly examined the effect of experiencing exposure to neighborhood disadvantage over multiple generations. This project will contribute to filling this gap in research on multigenerational neighborhood effects.

The Current Project: This paper has three main contributions. First, we analyze a largely unused dataset in the realm of multigenerational neighborhood effects: the restricted NLSY 1979 cohort (NLSY79) and the public-use Child and Young adult cohort (NLSY79:CYA). The restricted tract level data from the NLSY79 are only accessible via a federal clearance procedure and on-site analysis at the Bureau of Labor Statistics in Washington, DC and are necessary because, when merged with Census data on neighborhood characteristics, they provide essential information about neighborhood conditions and family background factors across multiple generations.

Second, we employ a subjective measure of neighborhood conditions as our outcome of interest. Census tracts are typically used in neighborhood research and are a geographic unit perceived to provide an accurate depiction of the structural conditions that can impact individuals' outcomes across the life course (Jencks and Mayer 1990; Massey and Denton 1993; Wilson 1987). Scholars have utilized other geographies like commuting zones (e.g., Chetty et al.

[1] The U.S. Census Bureau uses a set of dollar value thresholds that vary by family size and composition to determine who is in poverty. In 2016, the poverty line was about $24,000 for a family of four.

2014) and block faces (e.g., Sharkey et al. 2014) in empirical investigations as well. However, new research has attempted to break away from these governmentally defined geographic units, instead relying on the subjects' own interpretation of their neighborhoods or boundaries contingent upon their physical movement throughout the day (for a discussion of activity space, see York Cornwell and Cagney 2017). A residential tract is unlikely to be the only context of influence. A subjective measure that relies on personal interpretation has the possibility to alter our understanding of how we conceptualize and measure neighborhood context, providing a qualitative distinction and contributing to the body of knowledge on extra local geographies.

Third, this dataset allows us to move beyond an exploration of the effects of parents' childhood context on their children's childhood context. We will look to the children's context in adulthood as well, expanding our multigenerational frame to indirectly include great-grandchildren. We therefore contribute to the emergent body of literature that is focusing on a four generational perspective of inequality (Mare 2011). We directly address the growing interest in the transmission of inequality across multiple generations and the hypothesis that neighborhood context yields multigenerational influence. Our analysis looks at neighborhoods through an intergenerational lens and moves beyond prior work that focuses on static measures of neighborhood quality or that which analyzes the transmission process solely from parents to children.

Data: We will assess our hypothesis by using the restricted NLSY79 geocoded Census tract data (1979-2014) and by merging it with the public-use NLSY79:CYA data (1986-2014). Finally, we will use Geolytics data to append Census tract characteristics to the NLSY79 tract identifiers. Because the Bureau of Labor Statistics (BLS) deems these data to be highly sensitive, we must travel to the BLS in Washington, DC to run all analyses for this project.

The merged NLSY data provide conditions for grandparents, parents, and grandchildren in the following way: data from NLSY79 respondents when they were under 18 provide information about adult conditions of the grandparents; data from the NLSY79 respondents when they were over 18 provide information about the adult neighborhood conditions of the parents; and data from the NLSY79:CYA when they were over 18 provide adult neighborhood conditions for grandchildren.

There are three family-level mobility trends across neighborhood context that we will examine. A *descending family* is one where the parent was situated in an advantaged neighborhood context during childhood, but his/her children grew up in a disadvantaged neighborhood. An *ascending family* is one where the parent grew up in a disadvantaged neighborhood, but his/her children did not, and are instead situated in an advantaged neighborhood context. These patterns represent a downwardly mobile and an upwardly mobile family, respectively. The cumulative effects of a static residential context can also be assessed, and a *rigid family* experiences a consistent childhood neighborhood context in both generations, conforming to the findings of Sharkey (2008).

Analytical Strategy: As our main predictor, we will use a multidimensional composite scale of neighborhood disadvantage using the following components of tracts: percent with a BA, percent unemployed, percent in poverty, percent of managers and professionals, percent not in the labor force, median housing value, and median income. As the main outcome, we use data on the subjective assessment of neighborhood conditions. These neighborhood characteristics are not bound by U.S. Census tract definitions. That is, the respondents define their own "neighborhoods" subjectively based on the following conditions: people do not respect rules/laws, crime and violence, abandoned/run-down buildings, parents do not supervise their children, people do not care/keep to themselves, and people cannot find jobs.

We will begin with traditional linear probability and logistic regression models to examine intergenerational and multigenerational neighborhood disadvantage. Intergnerational refers to the relationship between parent's childhood neighborhood and their children's adult neighborhoods. Multigenerational refers to the case where both parents and their children were exposed to childhood neighborhood disadvantage. We will extend Sharkey and Elwert's (2011) approach by examining the effect of intergenerational exposure to neighborhood disadvantage on individuals' adult outcomes (they only examined childhood cognitive development).

Next, we will use cousin fixed effects models to examine the link between intergenerational exposure to neighborhood disadvantage and subjective neighborhood assessment during adulthood. These models will allow for inferences about the multigenerational dimension of neighborhood inequality that address unobserved confounding that stems from time-invariant characteristics of extended families that are difficult to measure and control for. We will follow conventional methods to impute for any missing data (Allison, 2002; von Hippel, 2007).

Results: We have traveled to Washington DC to conduct basic analyses for the impact of multigenerational exposure to neighborhood disadvantage on grandchildren's adult subjective neighborhood assessment. These preliminary results demonstrate that exposure across two generations positively predicts a subjective assessment of neighborhood disadvantage in the grandchild's generation. That is, children whose parents and grandparents lived in disadvantaged neighborhood are more likely to also report living in a disadvantaged neighborhood based on their subjective assessment of their neighborhood context (compared to those whose parents and grandparents did not). We will be able to return to the BLS prior to PAA to continue with the analyses as needed.

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Table 1. Regression models for the impact of multigenerational exposure to neighborhood disadvantage on grandchildren's adult subjective neighborhood assessment

	Subjective Neighborhood Assessment			
	(1)	(2)	(3)	(4)
	Zero order	+ Parent's childhood characteristics	+ Child's childhood characteristics	+ Cousin fixed effects[a]
Parent neighborhood disadvantage only	0.28**	0.13	0.05	0.07***
	(0.09)	(0.09)	(0.09)	(0.02)
Child neighborhood disadvantage only	1.14***	0.95***	0.66***	0.05***
	(0.10)	(0.10)	(0.11)	(0.01)
Multigenerational exposure	1.17***	0.89***	0.57***	0.04*
	(0.08)	(0.09)	(0.10)	(0.02)
Constant	0.47***	0.73***	6.75***	0.95***
	(0.04)	(0.21)	(0.82)	(0.15)
Observations	5,710	5,710	5,530	5,950

a Logistic regression models are used in (1) - (3). A linear probability model is used when calculating cousin fixed effects in (4).
The reference category is neither parent nor child were exposed to neighborhood disadvantage.
Coefficients are shown.
Robust bootstrapped standard errors (in parentheses) are corrected for clustering.
†p < .10; *p < .05; **p < .01; ***p < .001
Source: NLSY 1979-2014 & NLSY CYA 1986-2014

Table 2. Interaction logistic regression models for the impact of multigenerational exposure to neighborhood disadvantage on children's adult subjective neighborhood assessment by race and ethnicity (NLSY:CYA 1986-2012)

	(1) + Parent's childhood characteristics	(2) + Child's childhood characteristics
Main effects		
Parent neighborhood disadvantage only	0.07	-0.02
	(0.13)	(0.14)
Child neighborhood disadvantage only	0.95***	0.72***
	(0.15)	(0.16)
Multigenerational neighborhood disadvantage	1.20***	0.92***
	(0.18)	(0.19)
Black	0.25*	0.28*
	(0.11)	(0.12)
Latino	0.37**	0.36*
	(0.14)	(0.14)
Interaction effects		
Black*Parent neighborhood disadvantage only	-0.07	-0.12
	(0.21)	(0.21)
Latino*Parent neighborhood disadvantage only	0.11	0.37
	(0.25)	(0.26)
Black*Child neighborhood disadvantage only	0.25	0.17
	(0.25)	(0.26)
Latino*Child neighborhood disadvantage only	-0.62*	-0.61*
	(0.26)	(0.27)
Black*Multigenerational neighborhood disadvantage	-0.39†	-0.41†
	(0.23)	(0.24)
Latino*Multigenerational neighborhood disadvantage	-0.80**	-0.66*
	(0.25)	(0.26)
Constant	0.65**	6.90***
	(0.23)	(0.81)
Observations	5,710	5,530

Note: Time-varying and time-invariant controls include mother's poverty, mother' weeks unemployed, number of children in the household, mother's logged household income, single parent, mother's education, mother's foreign born status, mother's AFQT score, whether or not the mother's household ever moved, child's sex, child's history with hard drugs, child's highest year of schooling, child's adult household income, child's adult unemployment history, child's adult neighborhood disadvantage.

The reference category is white; neither parent nor child were exposed to neighborhood disadvantage.

Coefficients are shown.

Robust bootstrapped standard errors (in parentheses) are corrected for clustering.

†p < .10; *p < .05; **p < .01; ***p < .001